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Filtering based multi-innovation extended stochastic gradient algorithm for Hammerstein nonlinear system modeling ☆

Ziyun Wang *, Yan Wang, Zhicheng Ji

Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education), Jiangnan University, Wuxi 214122, PR China

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ABSTRACT

This paper considers parameter estimation problems of Hammerstein finite impulse response moving average (FIR-MA) systems. In order to provide highly accurate parameter estimates and improve the convergence rate, a data filtering based multi-innovation extended stochastic gradient algorithm is presented to estimate the parameters of Hemmerstein FIR-MA systems by using the current innovation and past innovations. The simulation results show that the proposed algorithm can effectively estimate the parameters of the Hammerstein FIR-MA systems.

1. Introduction

Iterative and recursive parameter estimation methods are widely used as significant tools for establishing mathematical models of dynamical systems [1–5] and solving matrix equations [6–8]. Many identification methods have been developed for Hammerstein nonlinear models [9–13]. For instance, Ahmadi and Mojallali considered the implementation of Bezier–Bernstein polynomials and the Levenberg–Marquart algorithm for identifying multiple-input single-output Hammerstein models consisting of nonlinear static functions followed by linear dynamical subsystems [9]. Biagiola and Figueroa discussed identification problems of uncertain MIMO Wiener and Hammerstein models and applied the proposed approach to a distillation column [10]. Chen et al. studied gradient based estimation algorithms for Hammerstein systems with saturation and dead-zone nonlinearities by introducing an appropriate switching function [11].

Compared with the recursive least squares algorithm [14] and the least squares algorithm [15,16], the multi-innovation identification method is a novel parameter estimation method [17]. In the area of the multi-innovation identification, Ding and Chen presented multi-innovation gradient type identification algorithms from the viewpoint of innovation modification [18]. Wang et al. derived a residual based interactive stochastic gradient parameter estimation algorithm for controlled moving average models and studied its performance [19]. Liu et al. studied the convergence of the stochastic gradient identification algorithm of multi-input multi-output ARX-like systems by using the stochastic martingale theory [20]. Recently, several multi-innovation methods have been presented by Ding, including the interval-varying multi-innovation

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* Corresponding author.
E-mail addresses: wangzy0601@163.com (Z. Wang), yanwangjn@163.com (Y. Wang), zcji@jiangnan.edu.cn (Z. Ji).

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recursive least squares algorithm [21]. Han and Ding developed a multi-innovation stochastic gradient algorithm for multi-input multi-output systems [22]. Liu et al. presented an auxiliary model based stochastic gradient algorithm for multiple-input single-output systems by using the auxiliary model [23]. Wang and Ding combined the multi-innovation identification theory and the auxiliary model identification idea, and presented an auxiliary model based multi-innovation stochastic gradient algorithm for output error systems by expanding the scalar innovation to an innovation vector [24]. Wang et al. presented an auxiliary model-based recursive extended least-squares algorithm and an auxiliary model-based multi-innovation extended least-squares algorithm for Hammerstein OEMA systems by using the multi-innovation identification theory.

The filtering method is a class of new parameter estimation methods [25–28]. For example, Wang and Ding used an estimated noise transfer function to filter the input–output data and presented filtering based recursive least squares algorithms for controlled autoregressive autoregressive moving average systems. Xie et al. presented a filtering based recursive least squares method for the non-uniformly sampled Box–Jenkins system. This paper uses multi-innovation identification theory [18,21], expands the scalar innovation to an innovation vector and derives a multi-innovation extended stochastic gradient algorithm for Hammerstein nonlinear systems based on the data filtering theory.

Briefly, the rest of this paper is recognized as follows. Section 2 gives a system description for Hammerstein nonlinear finite impulse response moving average systems. Section 3 presents a data filtering based multi-innovation extended stochastic gradient algorithm by expanding the scalar innovation to an innovation vector. Section 4 provides an example for illustrating the results in this paper. Finally, some concluding remarks are offered in Section 5.

2. The system description

Let us define some notation first. $\hat{\boldsymbol{\theta}}(t)$ represents the estimate of $\boldsymbol{\theta}$ at time t; "$A =: X$" or "$X := A$" denotes "A is defined as X"; E is the expectation operator; the symbol $\boldsymbol{I}$ ($\boldsymbol{I}_n$) stands for an identity matrix of appropriate sizes ($n \times n$); $\mathbf{1}_n$ signifies an n-dimensional column vector whose elements are all unity; the norm of a matrix or a column vector $\boldsymbol{X}$ is defined by $\|\boldsymbol{X}\|^2 := \mathrm{tr}[\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}]$. For convenience, it is supposed that t is the current time in this paper.

Consider a Hammerstein nonlinear system described by an finite impulse response moving average (FIR-MA) model in Fig. 1.

$$y(t) = B(z)\bar{u}(t) + D(z)v(t), \tag{1}$$

$$\bar{u}(t) = f(u(t)), \tag{2}$$

where $u(t)$ and $y(t)$ are the system input and output, respectively, the output $\bar{u}(t)$ of a nonlinear block is the input of a linear block, $v(t)$ is a stochastic white noise with zero mean and a variance σ^2. From Fig. 1, the linear block is an FIR-MA model, the nonlinear block is a nonlinear function of a known basis $\boldsymbol{f} := (f_1, f_2, \ldots, f_{n_c})$ with coefficients $(c_1, c_2, \ldots, c_{n_c})$:

$$\bar{u}(t) = f(u(t)) = \sum_{i=1}^{n_c} c_i f_i(u(t)) = c_1 f_1(u(t)) + c_2 f_2(u(t)) + \cdots + c_{n_c} f_{n_c}(u(t)). \tag{3}$$

$B(z)$ and $D(z)$ are polynomials in the unit backward shift operator z^{-1} $[z^{-1}y(t) = y(t-1)]$, and defined by

$$B(z) := b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{n_b} z^{-n_b},$$
$$D(z) := 1 + d_1 z^{-1} + d_2 z^{-2} + \cdots + d_{n_d} z^{-n_d}.$$

Assume that the degrees n_b and n_d are known and $y(t) = 0$, $u(t) = 0, x(t) = 0$ and $v(t) = 0$ for $t \leqslant 0$.

Apparently, any pair $(f(\cdot), B(z))$ is not unique in the model in (1). For a nonzero constant α, the pair $(\alpha f(\cdot), B(z)/\alpha)$ would produce identical input and output measurements. To get unique parameter estimates, there are several ways to normalize the coefficients. Without loss of generality, one assumes that $b_1 := 1$ or the first coefficient of $f(\cdot)$ is 1 ($c_1 = 1$). In the paper, we adopt the second assumption [29] and normalize the coefficients with $\|\boldsymbol{c}\|$=1.

This paper discusses identification problems for Hammerstein systems by using the filtering theory. The objective is to present a multi-innovation technique to estimate the system parameters (b_i, c_i, d_i) from available input–output data and to evaluate the accuracy of the parameter estimates by simulation examples.

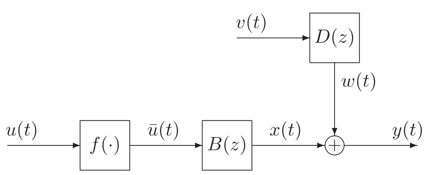

Fig. 1. The Hammerstein FIR-MA system.