ARTICLE IN PRESS

ISA Transactions xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

Research article

Identification of nonlinear Wiener-Hammerstein systems by a novel adaptive algorithm based on cost function framework☆

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ARTICLE INFO

Keywords:
Adaptive parameter identification
Wiener-Hammerstein
Filtering technique
Cost function

ABSTRACT

This paper investigates parameter identification of nonlinear Wiener-Hammerstein systems by using filter gain and novel cost function. Taking into account the system information is corrupted by noise, the filter gain is exploited to extract the system data. By using several auxiliary filtered variables, an extended estimation error vector is developed. Then, based on the discount term of the extended estimation error and the penalty term on the initial estimate, a novel cost function is developed to obtain the optimal parameter adaptive law. Compared with the conventional cost function which is composed of the square sum of output error, the proposed algorithm based on the cost function of this paper can provide faster convergence rate and higher estimation accuracy. Furthermore, the convergence analysis of the proposed scheme indicates that the parameter estimation error can converge to zero. The effectiveness and practicality of the proposed scheme are validated through the simulation example and experiment on the turntable servo system.

1. Introduction

In the industrial processes, the dynamics of most natural systems are nonlinear and can be sufficiently captured and approximated by nonlinear models. Among the plentiful nonlinear models, block-oriented models are one of most widely used nonlinear models due to its simple structure and the outstanding performance of describing the nonlinear behavior of practical systems [1,2]. The most popular systems of block-oriented models are Hammerstein systems and Wiener systems [3,4]. To describe the complex nonlinear systems, the above-mentioned systems can be extended to the Hammerstein-Wiener systems and Wiener-Hammerstein systems. Various identification approaches for first three systems gradually reaching maturity [5–8]. And the identification of the Wiener-Hammerstein systems attracts more attention in recent years [9,10] owing to the fact that which is popularly used for nonlinear systems modeling [11–13]. The focus of this paper is on the identification of Wiener-Hammerstein systems, as shown in Fig. 1, where $L_1(\cdot)$ and $L_2(\cdot)$ denote linear dynamic subsystems, respectively. The intermediate submodel $f(\cdot)$ is a nonlinear model.

The filtering technique is applied to extract the useful system information from noisy measurement data and to identify the system parameters based on the filtered system information [14–17]. In recent years, some filtering techniques for system identification have been published such as linear filter [16], robust H_∞ filter [18], Kalman-type filter [19], adaptive filter [20], etc. Yu et al. [19] applied the Taylor expansion to approximate the nonlinear submodel of the Hammerstein-Wiener systems, and proposed a recursive identification algorithm to identify the parameters of the considered systems based on modified extended Kalman filter approach. Bershad et al. [20] presented a least mean square adaptive filter algorithm to partially estimate the convolution of input and output linear filters for the Wiener-Hammerstein system with the Hermite polynomial, and then used the higher order terms of Hermite expansion to approximate the each of the linear filters. Finally, stochastic gradient recursion algorithm is proposed to identify all the unknown coefficients of the Hermite polynomial. However, the mentioned filter algorithms can work based on some assumptions, such as a priori knowledge is available [21,22], modeling uncertainties have a wide range of fields [23] and the filter is strictly positive real [24]. In order to relax the assumptions, the filter algorithm in Ref. [25] can be used as a good solution in which the filter parameter is developed without the assumptions on the system model. Inspired by the literature [25], the filter gain is presented to extract the system information of the considered system from noise-corrupted identification data in this paper.

As in previous works mentioned, many parameter identification approaches of Wiener-Hammerstein systems have been presented by

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https://doi.org/10.1016/j.isatra.2018.07.015
Received 27 December 2017; Received in revised form 20 April 2018; Accepted 13 July 2018

Please cite this article as: Li, L., ISA Transactions (2018), https://doi.org/10.1016/j.isatra.2018.07.015

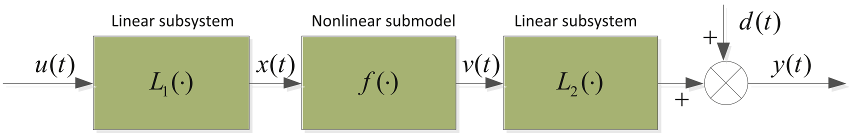

Fig. 1. Structural diagram of Wiener-Hammerstein systems.

both academics and engineers [10,26–28]. The major algorithms are iterative or recursive algorithm based on cost function [29], frequency estimation method [30], best linear approximation [31], subspace identification approach [32], kernel-type nonparametric estimation algorithm [10], etc. Vörös [29] exploited the switching function and decomposition technique to transform the Wiener-Hammerstein systems with backlash nonlinearity into a special identification model, which is identified through the usage of an iterative-type method with internal variable estimation based on the mean squares criterion. Schoukens et al. [31] proposed two stage identification algorithm to identify the Wiener-Hammerstein systems with polynomial nonlinearity. In first stage, the initial parameters of linear blocks and static nonlinearity are obtained by using the best linear approximation and linear least squares approach. In second stage, a Levenberg-Marquardt algorithm is presented to get all the final parameters based on the result of the first stage. Tan et al. [33] used the Wiener-Hammerstein systems with dead-zone nonlinearity to model the X-Y moving positioning stage by using several switch functions and key-term separation principle, and proposed a modified recursive general identification algorithm to estimate the parameters of the considered system.

Although the fact that the reported publications can produce efficient estimation or approximation accuracy by minimizing the corresponding cost function [10,29,34], cost function only includes the output error information while estimation error information and the initial estimate information are not considered [35,36]. In this paper, Based on the mentioned publications, a novel cost function is derived by using the extended estimation error information and initial estimate information. The contributions of this paper are summarized as follows:

(1) To reduce the effect of noise, the filter gain is applied to filter the system data, which can enhance the signal-to-noise ratio (the square root of the ratio of output and noise variance) and improve the performance of the identification algorithm. Compared with the mentioned filter algorithms, only one parameter is adjusted, which simplifies the design of the filter.
(2) The parameter update law is derived by minimizing a novel cost function. Compared with the conventional cost function, in this paper, cost function involves the extended estimation error information which can enhance the estimation accuracy, and the initial estimate information can improve convergence rate. Furthermore, the convergence analysis of the proposed algorithm indicates that the parameter estimation error can converge to zero.

The outline of this paper is listed as follows. The identification problem is stated in Section 2. In Section 3, an adaptive identification algorithm is developed. Section 4 discusses the convergence of the proposed algorithm. Subsequently, the simulation example and experiment are provided in Section 5 followed by Section 6 offers some conclusions.

2. Wiener-Hammerstein systems

As shown in Fig. 1, the Wiener-Hammerstein systems consist of the first linear subsystem L_1, that is acting on the input of the nonlinear submodel f. And then the output of nonlinear submodel acts on the input of the second linear subsystem L_2. Linear subsystems L_1 and L_2 can be described by

$$L_1\colon x(t) = \frac{A(z^{-1})}{B(z^{-1})}u(t) \tag{1}$$

$$L_2\colon y(t) = \frac{C(z^{-1})}{D(z^{-1})}v(t) + \frac{d(t)}{D(z^{-1})} \tag{2}$$

where $u(t)$ and $y(t)$ represent the input and output of the system, respectively. The intermediate signals $x(t)$ and $v(t)$ are immeasurable for user, $d(t)$ describes the system noise. The polynomials with the shift operator z^{-1} $[z^{-1}u(t) = u(t-1)]$. $A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$ and $D(z^{-1})$ are defined as follows:

$$\begin{aligned} A(z^{-1}) &= a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{n_a} z^{-n_a} \\ B(z^{-1}) &= 1 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{n_b} z^{-n_b} \\ C(z^{-1}) &= c_1 z^{-1} + c_2 z^{-2} + \cdots + c_{n_c} z^{-n_c} \\ D(z^{-1}) &= 1 + d_1 z^{-1} + d_2 z^{-2} + \cdots + d_{n_d} z^{-n_d} \end{aligned}$$

To realize the identification of the concerned systems, the following common assumptions are adopted [37]. (I) The orders of the polynomials n_a, n_b, n_c and n_d are known, but the coefficients a_i, $i = 1, 2, \ldots, n_a$, b_j, $j = 1, 2, \ldots, n_b$, c_p, $p = 1, 2, \ldots, n_c$ and d_q, $q = 1, 2, \ldots, n_d$ are unknown. (II) The linear subsystems L_1 and L_2 are coprime, that is to say, the linear subsystems are stable. (III) The systems are memoryless when $t \le 0$, i.e., $u(t) = 0$, $v(t) = 0$, $x(t) = 0$ and $y(t) = 0$ for $t \le 0$. (IV) To obtain a unique identification model, a_1 and c_1 are set as one.

Based on the nonlinearity types, the nonlinear submodel can be approximated by using smooth nonlinearity and non-smooth nonlinearity, respectively.

2.1. Smooth nonlinearity

The polynomial approximation is very widely used smooth nonlinearity description [38,39]. Assume the nonlinear submodel f is differentiable and described by the Taylor series expansion. The nonlinear submodel is written as follows

$$v(t) = v(0) + x(t)\frac{\partial v}{\partial x(t)}\bigg|_{x(t)=0} + x^2(t)\frac{\partial^2 v}{\partial x(t)^2}\bigg|_{x(t)=0} + \cdots \tag{3}$$

By choosing a finite order n_f, the following polynomial expression can be obtained

$$v(t) = f_1 x(t) + f_2 x^2(t) + \cdots + f_{n_f} x^{n_f}(t) \tag{4}$$

where f_m, $m = 1, 2, \ldots, n_f$ is constant coefficient.

Applying the key-term separation principle [40] to substitute (1) and (4) into (2), we obtain

$$y(t) = \varphi^T(t)\theta + d(t) \tag{5}$$

where the information vector $\varphi(t)$ and parameter vector θ are written as

$$\begin{aligned} \varphi(t) = [&u(t-2), \ldots, u(t-1-n_a), -x(t-2), \ldots, -x(t-1-n_b), x^2(t \quad , \\ &-1), \ldots, x^{n_f}(t-1), v(t-2), \ldots, v(t-n_c), -y(t-1), \ldots, -y(t-n_d)]^T \end{aligned}$$

$$\theta = \left[f_1 c_1 a_1, \ldots, f_1 c_1 a_{n_a}, f_1 c_1 b_1, \ldots, f_1 c_1 b_{n_b}, c_1 f_2, \ldots, c_1 f_{n_f}, c_2, \ldots, c_{n_c}, d_1, \ldots, d_{n_d}\right]^T$$

where $a_2 = f_1 c_1 a_2 / f_1 c_1 a_1, \ \ldots, a_{n_a} = f_1 c_1 a_{n_a} / f_1 c_1 a_1, b_1 = f_1 c_1 b_1 / f_1 c_1 a_1, \ \ldots, b_{n_b}$
$= f_1 c_1 b_{n_b} / f_1 c_1 a_1, f_1 = f_1 c_1 a_1, f_2 = f_2 c_1, \ \ldots, f_{n_f} = f_{n_f} c_1$