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Research article

A fast iterative recursive least squares algorithm for Wiener model identification of highly nonlinear systems

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ABSTRACT

In this paper, an online identification algorithm is presented for nonlinear systems in the presence of output colored noise. The proposed method is based on extended recursive least squares (ERLS) algorithm, where the identified system is in polynomial Wiener form. To this end, an unknown intermediate signal is estimated by using an inner iterative algorithm. The iterative recursive algorithm adaptively modifies the vector of parameters of the presented Wiener model when the system parameters vary. In addition, to increase the robustness of the proposed method against variations, a robust RLS algorithm is applied to the model. Simulation results are provided to show the effectiveness of the proposed approach. Results confirm that the proposed method has fast convergence rate with robust characteristics, which increases the efficiency of the proposed model and identification approach. For instance, the FIT criterion will be achieved 92% in CSTR process where about 400 data is used.

1. Introduction

Empirical models based on their input-output data are used widely for process control, because it is often difficult to obtain a reliable mechanistic model based on first principle modeling [1,2]. One of the popular kinds of these models is offline model estimation where the parameters vector θ is estimated by using N sets of input-output data. These models are estimated based on a particular situation of a plant. However, naturally some characteristics of plants are changed over time due to several reasons like, aging, disturbance appearance, failure in hardware, modification of operating points/ranges, strategies etc. [3]. Therefore, the designed controller based on the estimated model does not remain valid when the time evolves. This problem reveals the importance of online identification where the objective is to study the estimated model behavior close to the real plant characteristics during the time.

Recursive methods can be used for estimating the model parameters of dynamic systems. Recursive Least Squares (RLS) method is the most popular online parameter estimation in the field of adaptive control. The origin of the recursive version of least squares algorithm can be traced back to [4]. The linear RLS is discussed a lot in literatures and different aspects of this algorithm are studied [5–8]. In [9], iterative least squares algorithm and recursive least squares algorithm for identifying moving average systems have been proposed.

In practice, most systems have nonlinear behavior and therefore linear methods cannot be useful in many nonlinear plants. As a result, nonlinear system identification has become an active research topic and wide variety of techniques has been introduced [10–12]. Among different system identification structures, the so-called block-oriented models have been found very useful in modeling nonlinear systems such as chemical processes, biological and physiological systems [13]. These particular types of nonlinear models have many advantages over other nonlinear structures like neural networks in terms of minimal parameterization, computational time, initial model parameter and physical insight [14]. Hammerstein model (a linear dynamic block following a static nonlinear block) and Wiener models (a linear dynamic block preceding a static nonlinear block) are the most commonly used block-oriented models for nonlinear system identification. In this paper, the Wiener model is considered as a powerful tool to identify systems with nonlinearity in the output. Wiener models have been extensively employed in many practical applications [15,16]. For decays, Wiener models have been found as an attractive field of study in system identification literatures [17–19].

In this regard, the problem of Wiener model identification has been investigated in different manner. One of the common challenges in nonlinear identification is that the model may not be linear in parameter (LIP), and hence the computation to estimate the parameters will be difficult. In order to address this issue, different approaches have been proposed. For example, in [20], an

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iterative algorithm for identifying nonlinear functions is discussed where a gradient based iterative algorithm and Newton iterative algorithm are used to identify the parameters of the model. A least squares-based identification algorithm and a gradient based iterative identification algorithm are derived in [21] for Wiener systems which tries to separate a bilinear cost function into two linear cost functions. However, one of the significant challenges in gradient based approaches is that the algorithm may get trapped in local minima. Moreover, as represented in [21], the least squares-based approach has faster convergence rate than gradient based algorithm. Ding et al. in [22], proposed an RLS algorithm for a class of output nonlinear systems based on model decomposition. Nevertheless, the proposed algorithm can only consider identification problem for a class of systems whose nonlinear parts are a nonlinear function of previous output [22]. In [23], recursive extended least squares (RELS) estimation for a class of Wiener nonlinear systems with moving average noises is proposed. This algorithm is applicable just for the systems with invertible nonlinear part. In [15], an RLS identification algorithm for another class of Wiener models based on an auxiliary model with invertibility assumption of nonlinear part is presented. The proposed algorithm in the last paper is not suitable for highly nonlinear plants. In [24], an offline identification approach for Wiener systems with finite impulse response (FIR) dynamics and non-invertible polynomial nonlinearities is proposed. In addition, by multi-index notation, the products of coefficients of nonlinearity and linear dynamic part are estimated. Then, to extract the multiplied coefficients, four methods are proposed. However, in this paper a simpler fast online identification algorithm for models with non-invertible nonlinear blocks will be presented.

In this paper, an ERLS identification algorithm based on a proposed Wiener model with Auto Regressive Moving Average (ARMA) noises is presented. The ARMA(X) models are very powerful tools, which can estimate the LTI block of Wiener models as well as the dynamic of the colored noise. In practice, ARMA models have been used successfully in many applications and promising results have been obtained [25–28].

The proposed algorithm in this paper is relatively fast in training and uses a few input-output dataset to estimate the parameter vectorθ. The previous Wiener systems utilize the inverse of nonlinear part to estimate θ, where bring some limitations about invertibility of nonlinear block. Conversely, in this paper due to the estimation of intermediate signal, the inversion of nonlinear block is not required. Furthermore, the presented model is more robust against parameter uncertainties than the previous approaches, where a robust RLS algorithm with dead zone weighting factor is applied to the presented model in order to increase the robustness of the proposed approach. The ability of the proposed Wiener model makes this method useful even for highly nonlinear systems. The simulations on three different nonlinear systems indicate that the proposed algorithm identifies the Wiener systems faster and more precisely compared to the other previous methods.

2. Model description

Consider a Wiener model shown in Fig. 1. The model consists of a linear dynamic model followed by a static nonlinear block, where $u(k)$, $x(k)$, $y(k)$ and d are input signal, non-measurable intermediate signal, output signal and time delay respectively.

In this paper the dynamic linear part is defined as

$$x(t) = q^{-d}\frac{B(q^{-1})}{A(q^{-1})}u(t). \tag{1}$$

where $A(q^{-1})$ and $B(q^{-1})$ are polynomials in backwards-shift operator q^{-1} which are defined as follows:

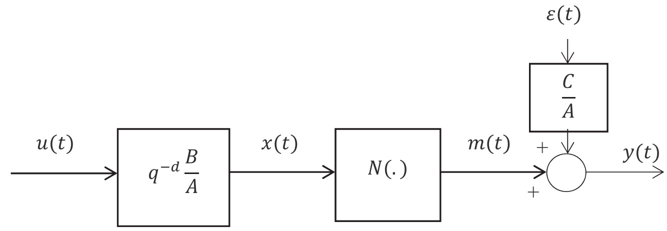

Fig. 1. A Wiener Model.

$$A(q^{-1}) = 1 + a_1q^{-1} + a_2q^{-2} + \cdots + a_{n_a}q^{-n_a}, \tag{2}$$

$$B(q^{-1}) = b_0q^{-1} + b_1q^{-2} + \cdots + b_{n_b}q^{-n_b}. \tag{3}$$

and the static nonlinear block is assumed to be the sum of polynomials up to order n_γ as

$$m(t) = N\big(x(t)\big) = \gamma_1x(t) + \gamma_2x(t)^2 + \cdots + \gamma_{n_\gamma}x(t)^{n_\gamma}. \tag{4}$$

$\varepsilon(t)$ is zero mean white noise with variance σ_ε^2 and

$$C(q^{-1}) = 1 + c_1q^{-1} + c_2q^{-2} + \cdots + c_{n_c}q^{-n_c}. \tag{5}$$

a_is, b_is, c_is and γ_is are unknown parameters but the order of polynomials are assumed to be known which indicates that the structure of the Wiener model is pre-specified, and an estimated value of plant time delay is available.

Without loss of generality, let the first coefficient of nonlinear block, γ_1, be unity. According to Fig. 1 and by substituting (1) in (4) one can write

$$y(t) = q^{-d}\frac{B(q^{-1})}{A(q^{-1})}u(t) + \gamma_2x(t)^2 + \cdots + \gamma_{n_\gamma}x(t)^{n_\gamma} + \frac{C(q^{-1})}{A(q^{-1})}\varepsilon(t). \tag{6}$$

Multiplying both sides of (6) by $A(q^{-1})$, it can be rewritten as

$$\begin{aligned} y(t) = {} & (1 - A(q^{-1}))y(t) + q^{-d}B(q^{-1})u(t) + A(q^{-1})\gamma_2x(t)^2 + \cdots \\ & + A(q^{-1})\gamma_{n_\gamma}x(t)^{n_\gamma} + C(q^{-1})\varepsilon(t). \end{aligned} \tag{7}$$

The information and vector of parameters are defined as

$$\begin{aligned} r(t) = {} & [-y(t-1) - y(t-2) \cdots -y(t-n_a)\, u(t-d-1)\, u(t-d-2). \\ & \cdots u(t-d-n_b)x(t)^2 \cdots x(t-n_a)^2 x(t)^3 \cdots x(t-n_a)^3 \cdots \\ & x(t)^{n_\gamma} \cdots x(t-n_a)^{n_\gamma}\varepsilon(t-1) \cdots \varepsilon(t-n_c)]^T \end{aligned} \tag{8}$$

$$\theta = [a_1a_2 \cdots a_{n_a}b_0 \cdots b_{n_b}\gamma_2a_1\gamma_2 \cdots a_{n_a}\gamma_2 \cdots a_1\gamma_{n_\gamma} \cdots a_{n_a}\gamma_{n_\gamma}c_1 \cdots c_{n_c}]^T \tag{9}$$

Thus, Eq. (7) can be rewritten in vector form as

$$y(t) = r(t)^T\theta + \varepsilon(t). \tag{10}$$

where the objective is to estimate the parameter vector θ.

3. Identification algorithms

In this section, two online identification algorithms are proposed to identify the model represented in previous section.

3.1. RLS Algorithm

In least squares method, the objective is to find estimation of parameter vector $\hat{\theta}$ which is obtained through minimization of the following cost function: