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Identification of discrete-time output error model for industrial processes with time delay subject to load disturbance

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ABSTRACT

In this paper, a bias-eliminated output error model identification method is proposed for industrial processes with time delay subject to unknown load disturbance with deterministic dynamics. By viewing the output response arising from such load disturbance as a dynamic parameter for estimation, a recursive least-squares identification algorithm is developed in the discrete-time domain to estimate the linear model parameters together with the load disturbance response, while the integer delay parameter is derived by using a one-dimensional searching approach to minimize the output fitting error. An auxiliary model is constructed to realize consistent estimation of the model parameters against stochastic noise. Moreover, dual adaptive forgetting factors are introduced with tuning guidelines to improve the convergence rates of estimating the model parameters and the load disturbance response, respectively. The convergence of model parameter estimation is analyzed with a rigorous proof. Illustrative examples for open- and closed-loop identification are shown to demonstrate the effectiveness and merit of the proposed identification method.

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1. Introduction

Unexpected or time-varying load disturbance is often encountered when performing identification tests for industrial processes [1–3], e.g. an inherent type load disturbance arising from the mold cavity pressure affects the injection velocity to fill up the mold cavity during the filling process of injection molding [4]. Unknown load disturbance may propagate throughout the process and blur the output response when performing an identification test, causing undesired identification error [2–5]. Bias-eliminated model identification against load disturbance has therefore become increasingly appealed in the recent years [6,7]. Different identification tests have been explored to deal with load disturbance. To enumerate a few, for the use of step response test, a time integral identification method [8] was proposed to eliminate the influence from stochastic or static type load disturbance. A robust step response identification algorithm was developed for unbiased parameter estimation against unexpected deterministic type load disturbance [9], by using the transient response data obtained by adding and subsequently removing a step change to the process input. With a pulse type input excitation, a two-stage identification algorithm was developed to cope with a specific class of load disturbance with a continuous spectrum of amplitude [10]. The approach was further extended to deal with periodic disturbance by using multiple sinusoidal excitations [11]. For the use of a closed-loop relay feedback identification test subject to static type load disturbance, a frequency domain transfer function identification method was proposed based on using the symmetric property of output response to eliminate the influence from such load disturbance [12]. By comparison, a so-called A-locus analysis method was presented to identify integrating and unstable processes subject to static type load disturbance [13]. However, a prior knowledge of the occurrence of load disturbance or its dynamics is needed to apply these identification methods, which may not be available in engineering applications subject to unknown load disturbance.

In discrete-time domain, a few output error (OE) model identification algorithms were presented to deal with stationary stochastic load disturbance for both open-loop and closed-loop identification tasks in the literature [5,14]. In cases where both the system input and

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output suffer from colored noises, errors-in-variables methods were developed to procure consistent estimation [15,16]. In the presence of unknown but bounded disturbance, an error-bounded parameter estimation algorithm was proposed based on using a membership set [17]. A refined instrumental variable (RIV) approach was recently developed by using a unified operator to estimate the Box–Jenkins model [18]. For the presence of non-stationary disturbance, a bias compensation identification algorithm [19] was given to obtain an extended ARMAX or OE model with good accuracy, by using a variable forgetting factor to estimate the model parameters and disturbance. For time delay systems, only a few papers presented discrete-time domain identification methods for obtaining an OE model with an integer type delay parameter, due to the difficulties for identifying the linear model parameters together with an integer type delay parameter that involves mixed-integer programming, which was recognized to be a non-convex problem for parameter estimation [20–22].

In this paper, to deal with unknown load disturbance having deterministic dynamics, a discrete-time domain OE model identification method is proposed for industrial processes with time delay response, to facilitate computer-aided control design for implementation. The output response to such load disturbance is viewed as a dynamic parameter which is lumped into the model parameters for estimation. To solve the above non-convex problem for parameter estimation, a one-dimensional searching strategy is given by minimizing the output prediction error to determine the optimal integer type delay parameter. An auxiliary model is constructed to realize consistent estimation of the model parameters against stochastic noise, in consideration of that the standard recursive least-squares (RLS) algorithm cannot guarantee consistent estimation of an OE model [23]. Moreover, dual forgetting factors are introduced to expedite the convergence rates of estimating the model parameters and the load disturbance response, respectively, with tuning guidelines to avoid the 'wind-up' of estimation error arising from using a constant forgetting factor as adopted in a traditional RLS algorithm, in particular for using a poor excitation for identification [24–27]. The convergence and unbiased estimation of the proposed algorithm is analyzed with a rigorous proof. The paper is organized as follows. In Section 2, the identification problem is presented. In Section 3, the proposed identification together with an application to identify an injection molding process model under time-varying load disturbance are presented in Section 5. Finally, conclusions are drawn in Section 6.

Throughout the paper, the following notations are used. Denote by \Re , \Re^n , and $\Re^{n \times m}$ the spaces of real number, *n*-dimensional real vector, and $n \times m$ real matrix, respectively. For any matrix $P \in \Re^{m \times m}$, P > 0 (or $P \ge 0$) means *P* is a positive (or semi-positive) definite matrix. For $P \in \Re^{m \times m}$ of full rank, denote by P^{-1} the inverse of *P*, by P^T the transpose of *P*, and by tr(P) the matrix trace. Denote by $\|P\|_2$ the Euclidean norm of $P \in \Re^n$. Denote by $\rho(P)$ the eigenvalue of *P*, and by $\rho_{\min}(P)$ and $\rho_{\max}(P)$ the minimum and maximum, respectively. The identity/zero vector or matrix with appropriate dimensions is denoted by $\mathbf{I}/\mathbf{0}$, where \mathbf{I}_m indicates $\mathbf{I}_m \in \Re^{m \times m}$ and $\mathbf{0}_{m \times n}$ for $\mathbf{0}_{m \times n} \in \Re^{m \times n}$. Denote by E[g] the mathematical expectation operator with respect to $g \in \Re^n$. Denote by $\hat{\alpha}$ the estimated value of $\alpha \in \Re^m$. Denote by z a discrete-time operator, i.e. $z^{-1}u(t):=u(t-1)$.

2. Problem description

When performing an identification test for a sampled system with time delay subject to load disturbance and measurement noise, the output response can be generally described by the following discrete-time OE model with an integer type delay parameter,

$$\begin{cases} x(t) = \frac{B(z^{-1})}{A(z^{-1})} z^{-d} u(t) \\ y(t) = x(t) + \xi(t) + v(t) \end{cases}$$
(1)

where d is an integer type delay. The polynomials $A(z^{-1})$ and $B(z^{-1})$ are coprime with the following forms,

$$A(z^{-1}) = 1 + a_1 z^{-1} + \dots + a_{n_a} z^{-n_a}$$
$$B(z^{-1}) = b_1 z^{-1} + \dots + b_{n_b} z^{-n_b}$$

All zeros of $A(z^{-1})$ are assumed to be inside the unity circle, i.e. the system is asymptotically stable. Denote by u(t), x(t) and $\xi(t)$ the excitation signal, noise-free response, and load disturbance response, respectively. The output measurement noise is denoted by v(t), which is usually assumed to be a Gaussian white noise with zero mean and unknown variance denoted by σ_v^2 .

Generally, it is assumed that the system is causal, i.e. y(t) depends on u(s) for $s \le t$, but not on future values of u(t) and v(t), while v(t) is uncorrelated with the input sequence, u(t). Assume that u(t) = 0, y(t) = 0, and v(t) = 0 for $t \le 0$, indicating the initial zero/steady state for identification.

For identifiablity, $\xi(t)$ resulting from load disturbance having deterministic dynamics is considered herein. Stochastic load disturbance response is lumped into v(t) to treat with.

The identification objective is to estimate the above OE model parameters including an integer delay from sampled data, with a prior knowledge or assumption on the orders of n_a and n_b for model fitting. For unknown system dynamics, the optimal model order may be determined by using the Akaike information criterion (AIC), a hypothesis testing condition [14], or a cross-correlation function between the input and the univariate residual sequence [19], so as to check if a higher order model could result in better fitting in terms of the parsimony principle on the number of model parameters.

3. Proposed identification method

3.1. Linear model parameter estimation

Denote the linear model parameter vector and plant information vector, respectively, by

$$\theta_0 = [a_1, \cdots, a_{n_a}, b_1, \cdots, b_{n_b}]^T \in \mathfrak{R}^{n_0}$$

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