Journal of Process Control 25 (2015) 41–49

Contents lists available at ScienceDirect

Journal of Process Control

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

Bias-eliminated subspace model identification under time-varying deterministic type load disturbance

Tao Liu [a,*], Biao Huang [b], S. Joe Qin [c]

[a] Institute of Advanced Control Technology, Dalian University of Technology, Dalian, PR China
[b] Department of Chemical & Materials Engineering, University of Alberta, Edmonton, Canada
[c] Department of Electrical Engineering and Department of Chemical Engineering & Materials Science, University of Southern California, Los Angeles, CA, USA

ARTICLE INFO

Article history:
Received 27 May 2014
Received in revised form
11 September 2014
Accepted 23 October 2014
Available online 26 November 2014

Keywords:
Subspace identification
Orthogonal projection
Singular value decomposition
Extended observability matrix
Rank condition

ABSTRACT

Unexpected or time-varying deterministic type load disturbances are often encountered when performing identification tests in practical applications. A bias-eliminated subspace identification method is proposed in this paper by developing an orthogonal projection approach to guarantee consistent estimation on the deterministic part of the plant, in combination with a Maclaurin time series approximation on the output response arising from deterministic type load disturbance. The rank condition for such an orthogonal projection is disclosed in terms of the state-space model structure adopted for identification. Using principal component analysis (PCA), the extended observability matrix and the lower triangular Toeplitz matrix of the state-space model are explicitly derived. Accordingly, the plant state-space matrices can be retrieved from the above matrices through a shift-invariant algorithm. A benchmark example from the literature and an illustrative example of industrial injection molding are used to demonstrate the effectiveness and merit of the proposed identification method.

1. Introduction

Owing to the convenience of state-space plant description for multivariable control system design in modern industry [1–3], subspace identification methods have been intensively explored in the last two decades as surveyed in the references [4,5]. A few state-space model identification methods (SIMs) have been well recognized for practical application, for example, the canonical variate analysis (CVA) approach [6], the multiple-input-multiple-output error state space model identification (MOESP) method [7], the numerical subspace state space identification (N4SID) algorithm [8], and the instrumental variable method (IVM) [9]. The similarity on consistent estimation and differences in asymptotic properties between these SIMs were discussed in the literature [10]. Insightful analysis on the conditions for consistency and the asymptotic variances of the above SIMs can be found in the references [11–13]. To guarantee model veracity for real plants with stable response characteristics in nature, a few SIMs for obtaining a stable type state-space model were developed in the references [14–16]. A systematic approach for identifying a linear time-invariant state-space model of stable type together with proper model structure selection was presented in the bibliography [17]. The recent paper [18] proposed an SIM to obtain a minimal-dimension state-space model in the canonical form, thus connecting SIM with the classical transfer function parameter estimation that was primarily based on the prediction error method (PEM) [19]. For closed-loop subspace model identification, which is subject to correlation between the future control inputs and past outputs and measurement noise, the principal component analysis (PCA) approach [20,21] and the orthogonal projection methods [22,23] were proposed for bias-eliminated model identification. By comparison, a parallel implementation of the standard causal SIM algorithm [24] was developed for closed-loop consistent estimation, and subsequently, a predictor based subspace identification (PBSID) method [25] was given to circumvent the feedback issue in contrast to the CVA-type identification method. Analysis on the consistency and asymptotic properties of closed-loop SIMs can be found in the references [26–29].

Note that most of the existing SIMs including the aforementioned methods are based on identification tests with or without stochastic load disturbance. For the presence of deterministic type load disturbance, little research effort, however, has been devoted to the corresponding SIMs, except for a few references (e.g. [30]) which developed alternative identification methods based on a prior knowledge of disturbance dynamics. In many industrial

* Corresponding author. Tel.: +86 411 84706465.
E-mail addresses: liurouter@ieee.org (T. Liu), biao.huang@ualberta.ca (B. Huang), sqin@usc.edu (S.J. Qin).

http://dx.doi.org/10.1016/j.jprocont.2014.10.008
0959-1524/

applications, unknown or time-varying deterministic type disturbances are often encountered when performing identification tests, which will inevitably cause identification errors, especially for the static transfer function gain that reflects the steady-state balance. Note that the influence from a static type load disturbance cannot be removed exactly by change of the coordinates when measurement noise appears, in particular for a piecewise linear model identification of a nonlinear process. Moreover, waiting for no presence of load disturbance to perform an identification test can be quite troublesome and time-consuming in practical applications, especially for industrial processes with slow response dynamics.

This paper proposes a bias-eliminated SIM to tackle the above problem by developing an orthogonal projection method for consistent estimation on the deterministic part of the plant while using a Maclaurin time series approximation to mimic the output response arising from deterministic type load disturbance. Based on the state-space model structure adopted for identification, the persistent input excitation condition and the rank condition for performing an orthogonal projection based identification algorithm are disclosed to guarantee consistent estimation on the extended observability matrix and the lower triangular Toeplitz matrix of the plant state-space model. Consequently, a shift-invariant approach is adopted to retrieve the plant state matrices. Moreover, an alternative approach for the asymptotic variance analysis is given for practical application. A benchmark example from the literature is used to demonstrate the effectiveness and merit of the proposed method along with an illustrative application to an industrial injection molding process.

Throughout the paper, the following notations are used. Denote by $\Re^{n\times m}$ an $n\times m$ real matrix space. For any matrix $P\in\Re^{m\times m}$, $P>0$ means P is a 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 det(P) the matrix determinant; for $P\in\Re^{m\times n}$ of full row (or column) rank, denote by $P^{\dagger}$ the Moore–Penrose pseudo-inverse of P. Denote by rank (P) the rank of P, and by vec(P) the column vector obtained by stacking the columns in P on top of each other. The identity/zero vector or matrix with appropriate dimensions is denoted by $\boldsymbol{I}$/0, where $\boldsymbol{I}_m$ indicates $I_m\in\Re^{m\times m}$ and $\mathbf{0}_{m\times n}$ for $0_{m\times n}\in\Re^{m\times n}$. Denote by $E\{\bullet\}$ the mathematical expectation operator, and by $o(\bullet)$ an infinitesimal with respect to $(\bullet)$. Denote by $\otimes$ the Kronecker product between two matrices, and by $\delta_{i,j}$ the Kronecker delta function, with $\delta_{i,j}=1$ for $i=j$ and $\delta_{i,j}=0$ for $i\neq j$. Denote by $PE(u)$ the persistent excitation order of the input signal for identification, and by z a time shift operator to the sample data, i.e. $zu(t)$:=$u(t+1)$. Denote by Λ/V an orthogonal projection for $\Lambda\in\Re^{m\times j}$ onto the row space of $\mathrm{V}\in\Re^{n\times j}$, which is computed through $\Lambda/\mathrm{V}=\Lambda\mathrm{V}^T(\mathrm{V}\mathrm{V}^T)^{-1}\mathrm{V}$. Denote by $\Lambda^{\perp}\in\Re^{m\times(m-j)}$ the orthogonal complement matrix to the column space of $\Lambda\in\Re^{m\times j}$ if $m>j$.

2. Problem description

In practical applications subject to load disturbance and measurement noise, a plant to be identified is described generally by the following state-space model,

$$\begin{cases} x(t+1)=Ax(t)+Bu(t)+d(t)\\ y(t)=Cx(t)+Du(t)+\zeta(t)\end{cases} \tag{1}$$

where $x(t)\in\Re^{n_x}$, $u(t)\in\Re^{n_u}$, $y(t)\in\Re^{n_y}$, and (A, B, C, D) are the state matrices with appropriate dimensions; $d(t)\in\Re^{n_x}$ denotes load disturbance entering into the plant states, while $\zeta(t)\in\Re^{n_y}$ indicates the output measurement noise usually assumed to be a Gaussian white noise sequence with zero mean and unknown variance.

Since model identification uses the measured input and output data only, due to the fact that it is often difficult or even impossible to know exactly the internal states of the plant, we decompose the state response by

$$x(t)=x_u(t)+x_d(t) \tag{2}$$

where $x_u(t)$ and $x_d(t)$ denote the state response corresponding to $u(t)$ and $d(t)$, respectively, i.e.

$$\begin{cases} x_u(t+1)=Ax_u(t)+Bu(t)\\ y_u(t)=Cx_u(t)+Du(t)\end{cases} \tag{3}$$

$$\begin{cases} x_d(t+1)=Ax_d(t)+d(t)\\ y_d(t)=Cx_d(t)\end{cases} \tag{4}$$

Correspondingly, the output response can be expressed in terms of the linear superposition principle as

$$y(t)=y_u(t)+y_d(t)+\zeta(t) \tag{5}$$

where $y_d(t)\in\Re^{n_y}$ is a deterministic but unknown output response arising from deterministic type load disturbance. Note that $y_d(t)$ may also represent unmatched output response in the case of model mismatch for identification.

To identify the plant state matrices (A, B, C, D), we reformulate the plant description in the following form:

$$\begin{cases} x_u(t+1)=Ax_u(t)+Bu(t)\\ y(t)=Cx_u(t)+Du(t)+y_d(t)+\zeta(t)\end{cases} \tag{6}$$

The following assumptions are considered herein for model identification:

A1: The system described by (6) is asymptotically stable, i.e. all the eigenvalues of A lie inside the unit circle.

A2: The system description in (6) is minimal in the sense that (A, B) is reachable and (A, C) is observable.

A3: The output measurement noise, $\zeta(t)$, is independent of the plant state, $x(t)$, including the true output, $\hat{y}(t)=Cx_u(t)+Du(t)+y_d(t)$, and the input excitation, $u(t)$, i.e.

$$E\left\{\zeta(t)\begin{bmatrix}x^T(k) & \hat{y}^T(k) & u^T(k)\end{bmatrix}\right\}=0,\quad \forall_{t,k} \tag{7}$$

Given a stochastic sequence, $f(t)$, with a finite number of sampled data (N), denote the statistical mean by

$$\hat{E}[f(t)]=\frac{1}{N}\sum_{t=1}^{N}f(t)=E[f(t)]+o(1/N) \tag{8}$$

where $o(1/N)$ is infinitesimal when $N\to\infty$.

Regarding the initial sampling time, t_0, for collecting the response data, we define the 'past' and 'future' input Hankel matrices, respectively, by

$$U_p\triangleq\begin{bmatrix} u(t_0) & u(t_0+1) & \cdots & u(t_0+j-1)\\ u(t_0+1) & u(t_0+2) & \cdots & u(t_0+j)\\ \vdots & \vdots & \cdots & \vdots\\ u(t_0+i-1) & u(t_0+i) & \cdots & u(t_0+i+j-2)\end{bmatrix}\in\Re^{in_u\times j} \tag{9}$$

$$U_f\triangleq\begin{bmatrix} u(t_0+i) & u(t_0+i+1) & \cdots & u(t_0+i+j-1)\\ u(t_0+i+1) & u(t_0+i+2) & \cdots & u(t_0+i+j)\\ \vdots & \vdots & \cdots & \vdots\\ u(t_0+2i-1) & u(t_0+2i) & \cdots & u(t_0+2i+j-2)\end{bmatrix}\times\in\Re^{in_u\times j} \tag{10}$$

where $p=i$ and $f=2i-i=i$ denote the 'past' and 'future' data horizon adopted for computation.