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Hierarchical estimation algorithms for multivariable systems using measurement information

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ABSTRACT

With the development of industry information technology, many modelling methods have been focusing on the estimation problems of multivariable systems, especially for the multivariable systems with output error autoregressive noises, from input–output measurement information. Since such a system includes both a parameter vector and a parameter matrix, the conventional methods cannot be applied to parameter estimation and modelling. In order to solve this difficulty, a hierarchical least squares based iterative identification algorithm and a hierarchical generalized least squares identification algorithm are proposed. The basic idea is to decompose the system into two fictitious subsystems, to estimate the parameters of each subsystem, and to coordinate the associated items between the two subsystems. The simulation results indicate that the proposed algorithm is effective.

1. Introduction

With the development of industry technology and control theory, the single-variable systems have been unable to meet the needs in industry processes, and multivariable systems have been widely applied to describe production processes [2,26,29,39]. Compared with the single-variable systems, the multivariable systems have characteristics of strong relevance and coupling among the input and output variables, namely, each output of a multivariable system can be influenced by various input variables and vice versa. The research on multivariable systems has received much attention and a lot of work has been focused on the system analysis, controller design and system modelling and identification [1,3,4,13,35].

In the literature of multivariable systems, many identification methods have been reported [9,12,15], including the subspace identification methods [18,27], the maximum likelihood methods [28], the prediction error identification methods [35], to name but a few. Some of them are implemented based on the state-space models, e.g., the subspace identification methods, others are based on the linear difference matrix equations or discrete-time transfer functions matrix models [7]. Zheng derived a bias-eliminating least squares algorithm to estimate the parameters of the input–output representation for a multi-input single-output system with a white noise [38]. Pintelon et al. presented a maximum likelihood identification method for multivariable systems with Box–Jenkins model [28]. Liu et al. analyzed the convergence properties of stochastic gradient algorithm for multivariable ARX-like models [20], derived an iterative identification method for Box–Jenkins

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models [21], and presented an auxiliary model based identification algorithm [23] and multi-innovation identification algorithms [22,24].

The parameter estimation methods for the multivariable systems modelled by the linear difference matrix equations contain two categories: the recursive algorithms [17,19,32,34] and the iterative ones [8,21]. This paper considers the recursive and iterative identification problems for multivariable output error autoregressive (OEAR) models. The difficulties of such multivariable system identification are that the identification model contains one system parameter matrix and a parameter vector which consists of the coefficients of the characteristic polynomial. The main contributions of this paper lie in that a hierarchical least squares based iterative algorithm and a hierarchical generalized least squares algorithm are derived to identify the parameter vector and parameter matrix of the two subsystems interactively, by decomposing a multivariable system into two subsystems and based on the hierarchical identification principle [4–6,11].

The rest of the paper is organized as follows. Section 2 demonstrates the identification problem of the multivariable OEAR systems. Section 3 derives a hierarchical least squares based iterative algorithm. Section 4 gives a hierarchical generalized least squares algorithm for comparisons. Section 5 provides an example for verifying the effectiveness of the proposed algorithms. Finally, the concluding remarks are given in Section 6.

2. Problem formulation

Identification of multivariable systems has received much research attention. For example, Han et al. presented a hierarchical least squares based iterative algorithm for multivariable CARMA-like systems [16]:

$$\alpha(z)\boldsymbol{y}(t) = \boldsymbol{Q}(z)\boldsymbol{u}(t) + D(z)\boldsymbol{v}(t);$$

Zhang et al. derived a hierarchical gradient based iterative algorithm for multivariable output error moving average systems (i.e., multivariable OEMA systems) [30,36]:

$$\boldsymbol{y}(t) = \frac{\boldsymbol{Q}(z)}{\alpha(z)}\boldsymbol{u}(t) + D(z)\boldsymbol{v}(t),$$

where $D(z)$ is a polynomial in z^{-1}. On the basis of the work in [16,36], this paper discusses the hierarchical least squares based iterative identification algorithm and a hierarchical generalized least squares identification algorithm for the following multivariable OEAR-like systems,

$$\boldsymbol{y}(t) = \frac{\boldsymbol{Q}(z)}{\alpha(z)}\boldsymbol{u}(t) + \frac{1}{C(z)}\boldsymbol{v}(t), \tag{1}$$

where $\boldsymbol{y}(t) \in \mathbb{R}^m$ is the system output vector, $\mathbf{u}(t) \in \mathbb{R}^r$ is the system input vector, $\boldsymbol{v}(t) \in \mathbb{R}^m$ is a white noise vector with zero mean and unit variance, $\alpha(z) \in \mathbb{R}$ is the system characteristic polynomial in z^{-1} (z^{-1} is the unit backward shift operator: $z^{-1}\mathbf{y}(t) = \boldsymbol{y}(t-1)$), $\boldsymbol{Q}(z) \in \mathbb{R}^{m\times r}$ is a matrix polynomial in z^{-1}, and $C(z) \in \mathbb{R}$ is a polynomial in z^{-1}, and they are defined as

$$\begin{aligned}
\alpha(z) &:= 1 + \alpha_1 z^{-1} + \alpha_2 z^{-2} + \cdots + \alpha_n z^{-n}, \ \alpha_i \in \mathbb{R}, \\
\boldsymbol{Q}(z) &:= \boldsymbol{Q}_1 z^{-1} + \boldsymbol{Q}_2 z^{-2} + \cdots + \boldsymbol{Q}_n z^{-n}, \ \boldsymbol{Q}_i \in \mathbb{R}^{m\times r}, \\
C(z) &:= 1 + c_1 z^{-1} + c_2 z^{-2} + \cdots + c_{n_c} z^{-n_c}, \ c_i \in \mathbb{R}.
\end{aligned}$$

The diagram of this system is depicted in Fig. 1, where $\boldsymbol{x}(t)$ is the noise-free output vector, and $\boldsymbol{w}(t)$ is the noise model output vector, and

$$\boldsymbol{x}(t) := \frac{\boldsymbol{Q}(z)}{\alpha(z)}\boldsymbol{u}(t) \in \mathbb{R}^m, \tag{2}$$

$$\boldsymbol{w}(t) := \frac{1}{C(z)}\boldsymbol{v}(t) \in \mathbb{R}^m. \tag{3}$$

Eq. (1) can be written as

$$\boldsymbol{y}(t) = \boldsymbol{x}(t) + \boldsymbol{w}(t). \tag{4}$$

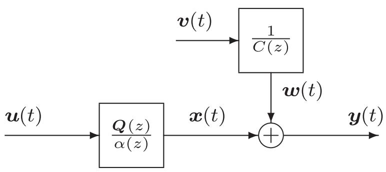

Fig. 1. The multivariable OEAR-like systems.

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