Identification of systems with slowly sampled outputs using LPV model

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A B S T R A C T

Identification of systems with slowly sampled output is studied. A linear parameter varying (LPV) model with multi-model structure is used to solve the problem. The output error (OE) method is used to estimate model parameters. Firstly, the local models and weighting functions are estimated separately using optimization methods. Then, a relaxation iteration method is developed to refine the parameters of the total model. For LPV model structure determination, an engineering approach is proposed that combines process knowledge with the so-called final output error criteria (FOE). The method is verified using both simulation data and industrial data. In the industrial case study, the LPV models give more accurate prediction of product qualities than that of a linear dynamic model and that of a static nonlinear model; the result also indicates the necessity of using test signals in soft-sensor development.

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1. Introduction

A system where inputs are sampled at a fast rate and some outputs are sampled slowly is common in the chemical process industry. For example, in a refinery or petrochemical process unit, in advanced process control (APC), the process inputs are sampled at 1 min; some outputs, typically product qualities, are sampled over 100 times slower than the inputs and the sampling time may vary. If the outputs are sampled uniformly at a slow rate, the system is called a dual-rate system. In this paper, we do not assume uniform output sampling, which means that this framework has a weaker assumption and the dual-rate system is a special case of this work. The problem studied here is to identify a fast sampled nonlinear dynamic model using the fast sampled inputs and slowly sampled outputs.

The background of such an identification problem is the so-called soft-sensor or inferential model, namely, to provide fast sample predictions of the slowly sampled outputs between their sampling intervals for process control and optimization. Presently, most of the soft sensors (inferential models) used in the process control are static models, see Ge and Song (2010). However, in chemical process control and optimization applications, dynamic data are used for static model identification, which will cause model errors; and additional errors will occur when the static model is used for quality prediction in dynamic situations. The aim of this work is to increase the model accuracy for soft-sensors by using nonlinear dynamic models.

To describe the systems with slowly sampled outputs using dynamic models, dual-rate system identification has received attention over the past years. Lu and Fisher (1988) made an early contribution where the authors used a polynomial transformation technique to obtain the lifted frequency-domain models of dual-rate systems. The lifting technique developed by Li et al. (2001, 2002) is another popular solution to the dual-rate system identification. The basic idea of this method is that a higher dimension lifted model is identified first and then the original fast rate model is extracted. Ding and Chen (2004) used an auxiliary model to predict the fast rate output and then identify the fast rate model.

An output error method was proposed by Zhu et al. (2009). Unlike other methods, this method identified the fast single-rate model directly from the dual-rate data by minimizing the sum of squared output error measured at the slow rate. It has been shown that the fast sampled model can be estimated with consistency using the fast inputs and slow outputs. This work extends the result to nonlinear systems.

In nonlinear system identification, linear parameter varying (LPV) model is studied and applied by both the academia and the industry. The terminology of LPV was first introduced by
2. LPV model description of systems with slowly-sampled output

Given a multi-input single-output (MISO) system with slowly and maybe irregularly sampled outputs. The input sampling time $T_u$ is the same as system sampling time; the output sampling time $T_y$ is much greater than $T_u$. $T_y$ may be time-variant, which means that the output can be sampled non uniformly. Denote the $m$ inputs as $u_1(t), u_2(t), \ldots, u_m(t)$ at sampling time $t$ and output as $y(t)$ at sampling time $t_y$. The input-output sampling of the system is illustrated in Fig. 1. If the sampling time $T_y$ is uniform as shown in case 1, then the system is the dual-rate system; case 2 indicates that the sampling time $T_y$ varies, hence the output is irregularly sampled. Denote $w(t)$ as the scheduling variable which is a measured process variable or can be calculated from measurable process variables (Huang et al., 2012). Throughout this paper, it is assumed that $w(t) \in [w_{\min}, w_{\max}]$, where $w_{\min}$ and $w_{\max}$ are low and high limits of $w(t)$. Then the MISO LPV model of system with slowly sampled outputs can be described as:

$$y(t_y) = \left[ \sum_{i=1}^{m} G_i(q, w)u_i(t) + v(t) \right]_{t=t_y}$$  (1)

where

$$G_i(q, w) = \left[ b_i^0(q)q^{-1} + \cdots + b_i^m(q)q^{-m} \right]_{1 + a_i^0(q)q^{-1} + \cdots + a_i^m(q)q^{-m}}$$  (2)

is the transfer function from $u_i$ to $y$, $d_i$ is the delay from the $i$th input to output, $v(t)$ is the unmeasured output disturbance, $q^{-1}$ is the backward shift operator, and $n$ is the order of the model. (1) and (2) form the LPV model of nonlinear system with slowly sampled output, which is called parameter-interpolation LPV model by Zhao et al. (2012).

However, Zhu and Xu (2008) pointed out that the LPV model in (1) and (2) is not easy to identify due to its complex structure and proposed a LPV model structure consisting of weighted local models, which is also called multi-model structure by Huang et al. (2012). Assume that the process has $l$ working points at:

$$w_{\min} \leq w_1 < w_2 < \cdots < w_l \leq w_{\max}$$  (3)

Denote the $l$ local linear working-point models as:

$$\hat{y}^1(t_y) = \left[ \sum_{i=1}^{m} \hat{C}_i^1(q)u_i(t) \right]_{t=t_y} , w = w_1$$

$$\hat{y}^2(t_y) = \left[ \sum_{i=1}^{m} \hat{C}_i^2(q)u_i(t) \right]_{t=t_y} , w = w_2$$

$$\vdots$$

$$\hat{y}^l(t_y) = \left[ \sum_{i=1}^{m} \hat{C}_i^l(q)u_i(t) \right]_{t=t_y} , w = w_l$$  (4)

where

$$\hat{C}_i^k(q) = \frac{b_i^0(q,w_k)}{\hat{A}_i(q,w_k)} = \left[ b_i^0q^{-1} + \cdots + b_i^m q^{-m} \right]_{1 + a_i^0q^{-1} + \cdots + a_i^m q^{-m}}$$  (5)

$k = 1, 2, \ldots, l$.

Then, the multi-model LPV model is adopted to represent the process along the operating trajectory as:

$$y(t_y) = \left[ \sum_{i=1}^{m} \alpha_k(w(t)) \sum_{i=1}^{m} \hat{C}_i^k(q)u_i(t) + v(t) \right]_{t=t_y}$$  (6)

where $\alpha_k(w(t)), k = 1, 2, \ldots, l$, are the weighting functions of the local linear models which are static functions of scheduling variable $w(t)$. The identification of multi-model LPV model can be divided into two steps: firstly local linear models are identified at fixed working points, then global model is obtained by interpolation via certain weighting functions.

For multi-input and multi-output (MIMO) processes, the procedure can be repeated for each output.
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