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Constrained two dimensional recursive least squares model identification for batch processes

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ABSTRACT

Recursive system identification, due to its easy online implementation and computation efficiency, has been widely used in many advanced process controls such as adaptive control and model predictive control (MPC). This paper proposes a novel two dimensional recursive least squares identification method with soft constraint (2D-CRLS) for batch processes. This method can improve the identification performance by exploiting information not only from time direction within a batch but also along batches. A soft constraint term is incorporated in the cost function to reduce the variation of the estimated parameters. A bound on weighting matrix has been established as the sufficient consistency condition in the paper together with a practical guideline for weights selection. Results based on the experimented data for injection molding, show the superiority of the proposed method over the conventional identification based on recursive least squares.

1. Introduction

System identification is an efficient and convenient approach to build dynamic models based on input and observed output data from real process with limited prior knowledge. It has been extensively studied for decades in academics with fruitful results, e.g. [1–3] and reference therein, and also widely applied in industry, e.g. [4,5] and reference therein.

Batch process is an important class of manufacturing techniques in modern industry. Due to its capability of manufacturing high-value-added products with superior versatilities, batch process is widely applied in many industries such as injection molding, semiconduct manufacturing and pharmaceutical industries. Compared with continuous process, batch process has its own characteristics, high nonlinearity, multi-phase, non-steady state, high repetitiveness, etc. Because of its unique properties and superior advantages, batch process is receiving increasing attentions in both academics and industries.

An accurate and reliable process model is crucial to the successful application of most advanced control strategies developed for batch process. A few successful system identification applications to batch processes have been reported. For example, state space model was identified online by RLS (recursive least squares) for the adaptive control of a fed-batch fermentation [6]. A cascade control structure was developed for the production of lactic acid and baker's yeast cultivation. An outer controller was used to search operating set-point and a inner controller to control the dynamics of bioreactors adaptively by RLS forgetting factor identification of the system parameters [7]. Based on RLS and second-order autoregressive exogenous model (ARX), Yang and Gao applied a self tuning regulator (STR) with pole placement and generalised predictive control (GPC) to control injection molding nozzle packing pressure and velocity, respectively, with high precision [8,9]. In [10], RLS was used to estimate the time-varying process dynamics for the GPC regulation of wood ash stabilisation. In [11], Shi et al. designed a robust iterative learning control integrated with feedback control for the control of injection velocity based on an identified second-order ARX model. They further proposed a two dimensional GPC controller based on an identified ARX model with an excellent outcome [12].

All the above works employed directly system identification approaches designed for continuous processes, ignoring the unique nature of batch processes. There have been very few publications on identification with consideration of batch natures, to the best knowledge of the authors'. Ma and Braatz developed an iterative way to off-line identify a model for a batch process by minimising

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Nomenclature

Arabic number

2D	two dimensional

Arabic letters

$A_k(t)$	parameter estimations weighting matrix
ARMAX	autoregressive moving average exogenous model
ARX	autoregressive exogenous model
a.s.	asympototically
$A_t(z)$, $B_t(z)$	output and input polynomials of ARX model
$b_k(t)$,$c_k(t)$	posterior and priori prediction error(scalars)
$E[x\|y]$	take conditional expectation of x with respect to y
$e(k, t)$	two dimensional white noise
$\{\mathcal{F}_{k,t}, k, t \in \mathbb{Z}_+\}$	increasing sequence of σ-fields
GPC	generalised predictive control
$J(k, t)$	cost function of t-time spot and kth batch
$P_k(t)$	input and output information matrix
RHS	right hand side
RLS	recursive least squares
$tr\{.\}$	trace of a matrix
SISO	single input single output
SNR	signal-to-noise ratio
STR	self tuning regulator
sup	upper bound
$u_k(t)$	control input of t-time spot and kth batch
$V_t(k)$	Lyapunov function of t-time spot and kth batch
w.r.t.	with respect to
$X_t(k)$	stochastic Lyapunov function
$y_k(t)$	control output of t-time spot and kth batch

Greek symbols

δ	batch-wise backward difference operator
$\delta_{i,j}$	Kronecker delta
$\epsilon_k(t)$,$\mu_k(t)$, $\rho_k(t)$, $\tau_k(t)$, $\omega_k(t)$	defined scalars
$\theta_0(t)$	vector of true system parameters
$\hat{\theta}_k(t)$	vector of parameter estimation on t-time spot and kth batch
$\tilde{\theta}_k(t)$	vector of estimation error on t-time spot and kth batch
λ_{min}, λ_{max}	minimum and maximum eigenvalue
$\phi_k(t)$	control input and output vector

Mathematical symbols

$\triangleq$	defined as
$\|.\|$	2-norms
$\|x\|_A^2$	x^TAx

Superscripts and subscripts

k	batch index
t	time index
T	transpose
0	true value

the model uncertainty [13]. Tayebi developed a two dimensional approach for some unknown parameters of the robot manipulator dynamic equations in a continuous type, but did not provide results on the performance of the estimator [14]. Chi et al. designed a discrete-time two dimensional system identification method integrated with adaptive iterative learning control (ILC), without consideration of some constraints between time spots within a cycle [15].

This article proposes a two dimensional online system identification method suitable for batch processes with soft constraints on time direction to reduce parameter variations. The main focus of the algorithm is a two dimensional cost function with a penalty term imposed to smooth estimation along time. 2D-CRLS is obtained by minimising a defined cost function. By virtue of martingale convergence theorem, a stochastic form of Lyapunov function is defined to yield consistency of the proposed 2D-CRLS. An upper bound of weighting matrix is obtained to guarantee robust convergence of the algorithm. Furthermore, a guildline for the selection of proper weighing matrix in application is provided, together with numerical simulations to demonstrate the advantages of the proposed system identification algorithm. The paper is organised as follows. Section 1 provides some necessary background information about this paper and introduces the overall structure of the method. Section 2 gives the problem setup and the derivation of the new recursive identification algorithm. Section 3 analyses consistency of the algorithm in stochastic scenario and gives the upper bound of weighting matrix for convergence insurance. In Section 4, the guildlines is established for the selecting of appropriate weights. Section 5 illustrates the effectiveness of the method through a numerical simulation. Finally, Section 6 draws the conclusion.

2. Problem description and algorithm derivation

The main objective of this work is to improve identification performance from batch to batch, by exploiting the nature of batch processes, which repetitively performs a given task over a finite period of time. A soft constraint is introduced to the cost function between two consecutive sample times to reduce estimation variation.

2.1. Problem description

Most batch processes are highly nonlinear in nature. A common practice to tackle this nonlinear dynamic nature is to develop a composite model over the time direction that is a combination of a set of linear models each with finite time duration. For example, in injection molding, the velocity vs. the hydraulic valve opening is a typical nonlinear process. Yang approximated it by a set of second-order ARX models along time direction [16]. Without loss of generality, our work can be easily extended to other type of linear models, e.g. ARMAX. This paper focuses on the identification of a time-varying ARX model as follows:

$$\begin{aligned} &y_k(t) + a_{1,0}(t)y_k(t-1) + a_{2,0}(t)y_k(t-2) + \cdots + a_{na,0}(t) \\ &y_k(t-na) = b_{1,0}(t)u_k(t-d) + b_{2,0}(t)u_k(t-d-1) + \cdots \\ &+b_{nb,0}(t)u_k(t-d-nb+1) + e(k,t) \end{aligned} \tag{1}$$

where $y_k(t)$ and $u_k(t)$ are respectively the system output and control input at the tth time in the kth batch, and $a_{i,0}(t)$ and $b_{i,0}(t)$ are the system parameters at the tth time. Subscript 0 indicates the true parameters of the system. d is the system delay, and na and nb stand for the order of output and input dynamics, respectively, $e(k, t)$ is a zero-mean white noise and

$$E[e(i,j)e(k,t)] = \sigma^2\delta_{i,k}\delta_{j,t} \tag{2}$$

where $\delta_{i,k}$ and $\delta_{j,t}$ are Kronecker delta. $\delta_{i,k}$ and $\delta_{j,t}$ are both equal to 1 if and only if $i=k$ and $j=t$, respectively.

Eq. (1) can also be represented as

$$y_k(t) = \phi_k^T(t)\theta_0(t) + e(k,t) \tag{3}$$

where

$$\begin{aligned} \phi_k(t) = {} & [-y_k(t-1) - y_k(t-2)\cdots - y_k(t-na)u_k(t-d)u_k(t-d-1) \\ & \cdots u_k(t-d-nb+1)]^T \end{aligned} \tag{4}$$