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Time-delay identification in dynamic processes with disturbance via correlation analysis

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ABSTRACT

A time-delay identification algorithm in closed-loop dynamic processes with disturbance based on maximum correlation analysis was proposed in this paper. To denoise the output data, the response of process disturbance was first estimated on routine data and then eliminated from the output. Next the incremental denoising process data were proposed to be used against the influence of system dynamic on the time-delay estimation. The correlations between the incremental input and different delayed output were computed and the delayed time corresponding to the maximum correlation was identified as the time-delay. The application in the Wood-Berry process and an industrial process showed the validity of the proposed algorithm.

1. Introduction

Many control strategies in industrial control theory are based on the process models which directly affect the control performance of the systems (Hong, Iplikci, Chen, & Warwick, 2014; Jin, Ryu, Sung, Lee, & Lee, 2014; Zhou et al., 2015). Time-delay is an important parameter in the process model which decides the time of implementing control action in model based control strategy (Jin et al., 2014). Too early adjustment of the control action would cause the significant overshoot and even severe oscillation, while too late controller regulation would result in long time deviation of the controlled variables (Sun, Song, & Xu, 2013a; Sun, Qin, Singal & Megan, 2013b). The disturbance can be overcome timely with less oscillation if the time-delay can be precisely estimated.

In many kinds of data-driven modeling methods, time-delay is not an explicit model parameter. For example, it is latent in the orders of inputs and outputs in the CARIMA model (Wang, Guo, & Zhang, 2001). In other modeling methods such as PLS (Partial Least Square), neural network, and so on, the time-delay is actually latent in the time match process of input and output data. Its identification attracts little attention in these modeling methods and is often artificially assumed in practice (Aljamaan, Westwick, & Foley, 2015; Sun et al., 2013a, 2013b; Wang et al., 2001). However, time-delay is an important parameter and is necessarily to be identified separately from other model parameters for most explicit controller tuning rules use the low order plus time-delay models (Ni, Xiao, & Shah, 2010).

An increasing number of techniques have been proposed for the time-delay identification problem, such as step response method (Cutler & Ramaker, 1980; Liu, Wang, & Huang, 2013) , relay feedback method (Jin et al., 2014; Liu & Gao, 2009; Skogestad, 2003), variable structure observer method (Drakunov, Perruquetti, Richard, & Belkoura, 2006), various optimization approaches (Gawthrop, Nihtilä, & Besharati-Rad, 1989; Loxton, Teo, & Rehbock, 2010; Tang & Guan, 2009; Yang, Iemura, Kanae, & Wada, 2007; Ren et al., 2005; Bedoui and Abderrahim, 2015; Michael, Christopher, & Lino, 2015; Lin, Loxton, Xu, & Teo, 2015), and correlation analysis method (Knapp & Carter, 1976; Ni et al., 2010; Talei and Chua, 2012; Sun, Jia, Du, & Fu, 2016; Cao, So, & Chan, 2017). These methods can be classified into two categories, model independent ones and model dependent ones.

The variable observer method and the extensively studied optimization based method are model dependent identification approaches. The analytical solution of estimated time-delay can be obtained by the variable observer method but it is on the condition of known state space model (Drakunov et al., 2006). Various optimization methods including the least square optimization (Gawthrop et al., 1989; Ren et al.,2005; Bedoui & Abderrahim, 2015; Yang et al., 2007; Michael et al., 2015), particle swarm optimization (Tang & Guan, 2009), gradient-based optimization (Lin et al., 2015; Loxton et al., 2010) and so on are extensively studied in the identification of model parameters. The optimization based methods optimally solve the time-delay parameters together with other model parameters to minimize the output prediction errors. Although the optimal prediction of output is obtained, there are some limitations for the optimization based identification of time-delay: (1) Model structure is required first before the parameters identification. In practice, the selected model structure

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is likely not match with the actual process model resulting in the incorrect estimation of time-delay. (2)Time-delay and other model parameters are identified simultaneously. There may be the case that not all the parameters are accurate but the predicted output is optimal in the training. People do hope to know the accurate time-delay in some cases such as determining the action time of feed-forward and the computation of incidence matrix in the multi-variables performance assessment. (3) These optimization-based methods are locally optimal for the limited samples, not the global optimum.

The step response method, relay feedback method and correlation analysis method belong to the model independent class. The first two methods both add additional excitation signals on the object and estimate the time-delay on the output response (Liu et al., 2013). It is not applicable for running processes because the excitation signal is not always allowed. Correlation analysis method estimates the time-delay by maximizing the correlation coefficients of two signals with time-delay (Cao et al., 2017; Sun et al., 2016). It is widely used in the estimation of time-delay between two static signals, for example, the time-delay between the rainfall and runoff time of rivers (Talei and Chua, 2015). For chemical processes, it is not applicable directly for the following reasons: (1) In generalized correlation analysis method and its modified versions, the maximum correlation reflects the time-delay between two variables at their stationary state and the dynamic between the two signals are not considered. But in the control system, the output variable changes dynamically in each regulating process and reaches the stable state after that. Hence, the dynamical regulating process must be considered in the identification of time-delay in chemical processes (Ni et al., 2010). Rad et al. suggested to overcome the dynamic problem by firstly identifying a dynamic model via the standard least square algorithm, and then producing a pseudo-pure delay system with no dynamic by the identified least square model to identify the time-delay via correlation technique (Rad, Lo, & Tsang, 2003). But the performance of time-delay estimation would severely depend on the precision of the least square model in this method. Ni et al. proposed a dynamic separation method against the influence of system dynamic on time-delay estimation, in which continuous wavelet transform was applied to separate the dynamics term from the time-delay and then correlation analysis method was combined to estimate the time-delay (Ni et al., 2010). (2) For closed-loop systems, the output signal is the sum response of control channel and disturbance channel. In the correlation analysis method, the data variation of disturbance channel inevitably interferes in the correlation of input and output variables, and thus results in the inaccuracy of the estimation. Some researchers have noticed the disturbance problem in the model identification and some excellent works have been done against the influence of load disturbance (Dong, Liu, Wang, Bao, & Cao, 2017; Kaya, 2006; Liu et al., 2013; Ljung, 2010). It is a pity that these load disturbance elimination methods are integrated in the identification algorithm and cannot be directly applied in correlation analysis method.

This paper tried to solve the dynamic and disturbance problem to make the correlation analysis method applicable in the time-delay identification of chemical processes. A disturbance signal estimation method by the routine input and output data was deduced based on part of Sun's work on process performance monitoring (Sun et al., 2013a, 2013b), which was used to separate the disturbance response from the output. To against the dynamic problem, the incremental input-output sequences were considered to express the system dynamic in the correlation analysis instead of separating the dynamic terms in most previous works.

The rest of the paper is organized as follows. The disturbance identification method based on closed loop data is introduced in Section 2. The maximum correlation calculation of delayed incremental sequence is described in Sect. 3. The overall algorithm for dynamic time-delay identification is discussed in Sect. 4. The application of the proposed algorithm in the simulation and the practical industrial process is illustrated in Sect, 5. Conclusions are made in Sect. 6.

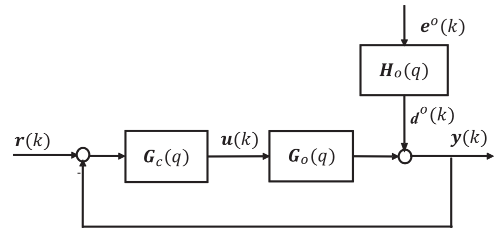

Fig. 1. Structure of closed-loop control system.

2. Disturbance signal identification

In industrial control processes, the outputs are the synthesized response of control channel and disturbance channel. Fig. 1 shows a SISO closed-loop control process whose output can be expressed as

$$y(k) = G_o(q)u(k) + H_o(q)e^o(k) \tag{1}$$

where $G_o(q)$ and $H_o(q)$ are the true but unknown process and disturbance models, $G_c(q)$ is a linear time-invariant (LTI) controller, q is the backward shift operator, $y(k)$ is the output of the control system, $r(k)$ is the set-point of $y(k)$, $u(k)$ is the input of control channel, $e^o(k)$ is the input of disturbance channel that assumed as a white noise with zero mean, $d^o(k)$ is the disturbance response of the system. For the sake of simplification, the backward shift operator q is omitted in the following description. From (Ljung, 1999), one-step ahead prediction of the output $\tilde{y}(kk-1)$ is

$$\tilde{y}(kk-1) = (1 - H_o^{-1})y(k) + H_o^{-1}G_o u(k)$$

and

$$y(k) = \tilde{y}(kk-1) + e^o(k) \tag{2}$$

where H_o and $G_o$are strictly causal. Denoting

$$1 - H_o^{-1} = \sum_{i=1}^{\infty} H_i q^{-i}$$

$$H_o^{-1}G_o = \sum_{i=1}^{\infty} G_i q^{-i}$$

where $H_i$and $G_i$are the coefficients. Thus Formula (2) becomes

$$y(k) = \sum_{i=1}^{\infty} H_i y(k-i) + \sum_{i=1}^{\infty} G_i u(k-i) + e^o(k) \approx \sum_{i=1}^{M} H_i y(k-i) + \sum_{i=1}^{N} G_i u(k-i) + e^o(k) \tag{3}$$

for sufficiently large truncation lengths M and N. It is clear from (3) that $e^o(k)$can be obtained from the routine closed-loop data $y(k)$and $u(k)$.

Define

$$y_p(k) = [y(k)y(k-1)\ldots y(k-p)]$$

$$e_p^o(k) = [e^o(k)e^o(k-1)\ldots e^o(k-p)]$$

$$u_p(k) = [u(k)u(k-1)\ldots u(k-p)]$$

where p is the sliding time window.

Define

$$Y_M(k-1) = [y_p(k-1)y_p(k-2)\ldots y_p(k-M)]^T$$

$$U_N(k-1) = [u_p(k-1)u_p(k-2)\ldots u_p(k-N)]^T$$

$$\overline{Z}_p(k) = [Y_M(k-1)U_N(k-1)]^T$$

where the dimensions of $Y_M(k-1)$,$U_N(k-1)$ and$\overline{Z}_p(k)$ are $M*p$,$N*p$ and $(M+N)*p$, respectively. Thus, (3) becomes

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