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ScienceDirect
Control Engineering Practice 15 (2007) 1577–1587
CONTROL ENGINEERING PRACTICE
www.elsevier.com/locate/conengprac

A stable self-learning PID control for multivariable time varying systems

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Available online 29 March 2007

Abstract

A stable self-learning PID (proportional + integral + derivative) control scheme for multivariable nonlinear systems with unknown dynamics is proposed in this paper. The control scheme is based on a neural network (NN) model of the plant. The NN model is adapted by an extended Kalman filter (EKF) to learn plant dynamic change, while the PID control parameters are adapted by the Lyapunov method to minimize squared tracking error. Therefore, the model output is guaranteed to converge to the desired trajectory asymptotically, and the plant output also tracks the desired trajectory due to model adaptation. The proposed scheme is evaluated by applying it to a simulated multivariable continuous stirred tank reactor (CSTR). The self-learning PID controller is also compared with a fixed parameter PID controller for a single-input single-output CSTR and the superiority of the self-learning PID is demonstrated.

Keywords: Self-learning PID; Adaptive NN models; Nonlinear systems; EKF; CSTR

1. Introduction

It is well known that PID (proportional + integral + derivative) controllers have dominated industrial control applications for a half of century, although there has been considerable research interest in the implementation of advanced controllers. This is due to the fact that the PID control has a simple structure that is easily understood by field engineers and is robust against disturbance and system uncertainty. As most of the industrial processes demonstrate nonlinearity in the system dynamics in a wide operating range, different self-tuning PID control strategies have been investigated in the past two decades.

Relay feedback is a simple and reliable test that keeps the process output under closed-loop control and makes it close to the operating point. Åstrom and Hagglund (1984) combined the strengths of both PID and relay control and invented the relay auto-tuner for a single-input single-output (SISO) PID controller. The tuner has been widely and successfully applied in industry, and further research to improve this technique has followed (Hang, Astrom, & Ho, 1993; Ho, Hong, Hansson, Hjalmarsson, & Deng, 2003; Park, Sung, & Lee, 1997). A tutorial given by Hang, Astrom, and Wang (2002) outlined the recent developments in this aspect. Some other techniques have also been used in developing auto-tuning PID controllers for SISO systems, such as the gain and phase margin-based method (Ho, Hang, & Cao, 1995). In addition, Kim and Han (2006) applied a robust PID-like neuro-fuzzy controller to induction motor servo drive systems. Tavakoli, Griffin, and Fleming (2006) presented tuning of decentralized PID controllers for TITO processes. Gyongy and Clarke (2006) described automatic tuning and adaptation of a PID controller.

Many industrial processes are inherently multivariable in nature and need multivariable control. Multivariable auto-tuning PID controllers have been in development for the past two decades. The early work includes a method for tuning the integral part of the multivariable PID controller developed by Davidson (1976). Pentinnen and Koivo (1980) proposed a method for tuning the P and I parts of the multivariable PID controller. The limitation of these methods is that some experimental and graphical

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doi:10.1016/j.conengprac.2007.02.004

procedures are required, which can be rather time consuming. Therefore, such methods are not suitable for on-line tuning. Zgorzelski, Unbehauen, and Niederlinski (1990), Loh, Hang, Quek, and Vasnani (1993) and Zhuang and Atherton (1994) developed multivariable PID controllers based on the method by Åstrom and Hagglund (1984). For the early multivariable PID control, Koivo and Tanttu (1991) gave a survey for its tuning techniques. These techniques primarily aim to decouple the plant at certain frequencies. Decentralized PID control structure has also been targeted with auto-tuning method developed by Halevi, Palmor, and Efrati (1997) and Palmor, Halevi, and Krasney (1993).

Methods based on on-line parameter estimation have also been proposed for the automatic tuning of PID regulators. Some authors proposed auto-tuning regulators based on minimum variance, pole placement or linear quadratic Gaussian (LQG) design methods. Gawthrop (1986) and Radke and Isermann (1987) proposed auto-tuning PID using adaptive parameter estimation methods. Hang and his co-workers have proposed auto-tuning PID regulators using alternative methods, including a knowledge-based PID auto-tuner (Lee, Hang, Ho, & Yue, 1993). Based on the method given in Nishikawa, Sannomya, Ohta, and Tanaka (1984), Ruano, Fleming, and Jones (1992) proposed a connectionist approach to PID auto-tuning, which used integral measures of the step response as the input to neural networks to determine the required PID parameter values. However, most of these methods are for SISO systems.

In this paper, a self-learning PID control for multivariable time varying systems is proposed based on a NN model of the plant. The NN model is on-line and updated with the EKF algorithm to learn plant dynamics change, while the PID controller parameters are updated based on the plant output predictions by the model. The proposed auto-tuning algorithm is operated iteratively and is developed using the Lyapunov method. Hence, the convergence of the tracking control is guaranteed. The proposed auto-tuning PID controller is evaluated by applying it to a simulated two-input two-output CSTR process. In order to compare the auto-tuning PID controller with a fixed parameter PID controller, a simulated SISO CSTR is used as a test bench. The superiority of the developed method over the fixed parameter PID is clearly shown.

2. Adaptive neural network model

2.1. The NN model

For a multivariable nonlinear sampled-data system represented by the following NARX (nonlinear auto-regressive with exogenous inputs) model,

$$y(k) = g[u(k-d-1), \ldots, u(k-d-n_u), y(k-1), \ldots, y(k-n_y)] + e(k), \tag{1}$$

where $u \in \Re^m$ and $y \in \Re^p$ are the sampled process input and output vector, n_u and n_y are the input order and output order, respectively, d denotes the process transmission delay and e is a noise vector, a multi-layer perceptron (MLP) network of the following form can be used to model the system.

$$\hat{y}(k) = \hat{g}[u(k-d-1), \ldots, u(k-d-n_u), y(k-1), \ldots, y(k-n_y)], \tag{2}$$

where $\hat{y} \in \Re^p$ is the estimated output by the NN model and $\hat{g}(\bullet)$ is an approximated nonlinear function of $g(\bullet)$. It has been previously proved (Funahashi, 1989) that if $g(\bullet)$ is sufficiently smooth, a network model can approximate it to any pre-specified accuracy, provided with enough numbers of hidden layer nodes. The commonly used structure of MLP network with one hidden layer of q neurons is adopted,

$$\hat{y}(k) = W^y \begin{bmatrix} o(k) \\ 1 \end{bmatrix}, \quad o(k) = f[z(k)], \quad z(k) = W^h \begin{bmatrix} x(k) \\ 1 \end{bmatrix}, \tag{3}$$

where $x(k) \in \Re^n$ is the network input vector and is given, according to (1), by

$$x(k) = [u(k-d-1)^{\mathrm{T}}, \ldots, u(k-d-n_u)^{\mathrm{T}}, y(k-1)^{\mathrm{T}}, \ldots, y(k-n_y)^{\mathrm{T}}]^{\mathrm{T}}, \tag{4}$$

where $n = mn_u + pn_y$, $o(k) \in \Re^q$ is the hidden layer output, $W^h \in \Re^{q\times(n+1)}$ and $W^y \in \Re^{p\times(q+1)}$ are the weight matrices in the hidden and output layers, respectively, $f(.)$ is the nonlinear activation function in the hidden layer, for which the sigmoid activation function is used in this study,

$$o(k) = \frac{1}{1+\mathrm{e}^{-z(k)}}.$$

2.2. EKF training algorithm

The extended Kalman filter (EKF) is chosen for the MLP network on-line updating in this study because this algorithm is much faster than the commonly used back-propagation algorithm. Back-propagation algorithm is the gradient descent method used for nonlinear optimization. The EKF algorithm applies the KF to the linearized nonlinear optimization problem. As the linear optimization using the KF is much faster compared with the nonlinear optimization using the back-propagation method, the EKF is adopted here in this research for MLP model updating.

There are two conditions for the EKF to be applied. One is that the process dynamics must be differentiable, or smooth, so that the dynamics can be linearized around the current operating point. The second condition is that all relevant input/output data should be measurable, and therefore are available for use by the EKF. Both conditions are satisfied in the updating of the MLP model and for the PID controller. The model parameters to be trained are weight matrices W^h and W^y. To enable these parameter