

Adaptive feed-forward control of thermal heating process

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Abstract: A novel adaptive inverse control (AIC) scheme is presented to facilitate on-line controller design of unknown nonlinear dynamic systems. The scheme is based on a control oriented model known as the U-model. The use of U-model alleviates the computational complexity of on-line nonlinear controller design that arises when using other modelling frame works such as NARMAX model. The effectiveness of the proposed scheme is illustrated by utilizing a laboratory scale nonlinear heating process as a test system.

Keywords: adaptive inverse control, thermal heating process, newton-raphson method

Classification: Science and engineering for electronics

References

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1 Introduction

In many industrial processes exact model of the plants to be controlled may not be known. Such processes also exhibit uncertain parameter variations due to environmental factors. As a result, researchers are paying much attention to develop adaptive control schemes to automatically adjust the uncertain parameters on-line (or, equivalently corresponding controller parameters) in the face of changing system dynamics. A survey of some adaptive control schemes to industrial applications is provided in [1]. Besides the parameter uncertainties, such systems are also characterized by considerable amount of nonlinear dynamics. Conventional linear control methods provide adequate control for such systems, but, for limited conditions and small ranges of operation. To deal with the problem, nonlinear controllers are utilized for control of such systems. A critical problem in nonlinear control is the selection of a model general enough to describe a wide range of nonlinear plants and provide a concise basis for controller design. An extensive discussion on this matter can be found in [2]. Amongst many, NARMAX model is one of the most commonly utilized and acknowledged for the purpose [3]. However, due to lack of maneuverable structure, controller design based on NARMAX model results into an inevitable computationally complex procedure. To reduce the design complexity, a control oriented model termed as the U-model is proposed in [4], where the nonlinear plant is represented as a polynomial in the current control term. Based on this model the plant inverse can be easily evaluated on-line using standard root solving algorithms such as the Newton-Raphson method.

In this work, an adaptive version of U-model is proposed to provide on-line feed-forward control of unknown nonlinear dynamic plants. The adaptive case is a natural extension of the U-model, which helps to govern changing dynamics of an unknown system. The scheme is examined by real-time application to a laboratory scaled nonlinear heating process. The experimental details and results are given in section 4.

2 The U-model structure

To develop the U-model, consider single-input single-output (SISO) nonlinear dynamic plants represented with a polynomial NARMAX model as:

$$y(t) = f[y(t-1), \dots, y(t-n), u(t-1), \dots, u(t-n), e(t), \dots, e(t-n)] \quad (1)$$

where $f(\cdot)$ is a nonlinear function, $y(t)$ and $u(t)$ are the output and input signals of the plant respectively at discrete time instant t while n represents the order of the plant. The error due to measurement noise, model mismatch, uncertain dynamics, plant variations is represented by $e(t)$.

Now by expanding the nonlinear function $f(\cdot)$ of the above equation as a polynomial with respect to $u(t-1)$ we can obtain the model as [4]:

$$y(t) = \sum_{j=0}^M \omega_j(t) u^j(t-1) + e(t) \quad (2)$$

where M is the degree of model input $u(t-1)$, $\omega_j(t)$ is a function of past inputs $u(t-2), \dots, u(t-n)$, outputs $y(t-1), \dots, y(t-n)$ and errors $e(t-1), \dots, e(t-n)$. Now the model can be treated as a pure power series of the input $u(t-1)$ with associated time varying parameters $\omega_j(t)$. The model exhibit a polynomial structure in the current control term $u(t-1)$, therefore, the control law will also result into a polynomial of $u(t-1)$. This is a clear advantage as many other methods lead to complex nonlinear equations.

To apply linear control system design methodologies to the nonlinear model a further transformation is performed to obtain the model as:

$$y(t) = U(t) \quad (3)$$

where

$$U(t) = \Phi[u(t-1)] + e(t) = \sum_{j=0}^M \omega_j(t) u^j(t-1) + e(t)$$

The expression of Eq. (3) is defined as the U-model.

2.1 The control law

Based on the U-model the control signal $u(t-1)$ can be easily obtained through a simple root-solving procedure such as the Newton-Raphson method from Eq. (3) as:

$$u_{q+1}(t-1) = u_q(t-1) - \frac{\sum_{j=0}^K \omega_j(t) u^j(t-1) - U(t)}{d \left[\sum_{j=0}^K \omega_j(t) u^j(t-1) \right] / du(t-1)} \quad (4)$$

where $U(t)$ is treated as root solver and the subscript q is the iteration index. However, there are two problems that can occur while applying the Newton-Raphson method. First, the possibility that the polynomial does not contain a real root. Second the denominator in Eq. (4) may become zero. To deal with these problems an improved computation of Newton-Raphson method is suggested in [5]. After applying the simple alterations the control scheme provides an adequate framework for adaptive control of nonlinear plants. The control law of Eq. (4) does not contain $e(t)$ because $\|e(t)\|_\infty \ll \|y(t)\|_\infty$, therefore, it can be ignored.

3 Proposed nonlinear adaptive inverse control scheme

AIC is a useful technique that provides model reference control for a wide range of dynamic plants. The approach involves open-loop control of a system by using a series adaptive controller. The controller adjusts itself to optimize the dynamic plant response and seeks to model the inverse of the plant to be controlled. The approach can be used for nonlinear as well as linear plants

and is convenient for the controller design and realization of a number of dynamic plant response [6]. The proposed AIC based scheme is depicted in Fig. 1.

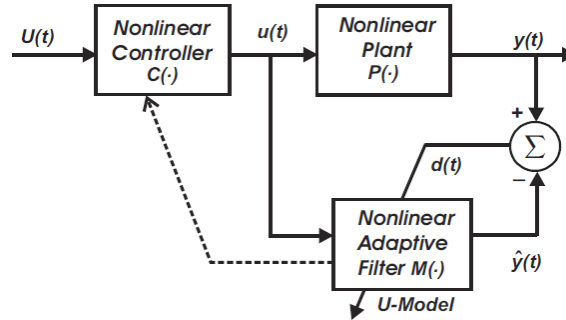


Fig. 1. Structure of proposed AIC scheme

The control structure includes an explicit plant model $M(\cdot)$ (an adaptive filter) in parallel with an open-loop stable/stabilized¹ plant $P(\cdot)$ while $\hat{y}(t)$ and $y(t)$ are the outputs at distinct time instants t respectively. The inverse controller is represented by $C(\cdot)$ with output control signal $u(t)$. The controller $C(\cdot)$ is to be designed so that $y(t)$ is kept as close as possible to command input $U(t)$. The symbol $d(t)$ represents the output difference between the plant $P(\cdot)$ and model $M(\cdot)$, i.e., $d(t) = y(t) - \hat{y}(t)$. The unknown parameters of $P(\cdot)$ are adapted by $M(\cdot)$ using normalized leaky least mean square (NNLMS) algorithm such that $d(t)$ is minimized. The model parameters, i.e., $\omega_j(t)$ are adapted at time index k by using following parameter update equation:

$$W_{k+1} = (1 - 2\mu\gamma)W_k + \frac{\mu}{\delta + \|X_k\|^2} X_k e_k \quad (5)$$

where W_k is a vector of adaptive filter parameters and X_k is the input vector given as:

$$\begin{aligned} W_k^T &= [\omega_{0k} \ \omega_{1k} \ \dots \ \omega_{nk}] \\ X_k &= [\varphi_{0k} \ \varphi_{1k} \ \dots \ \varphi_{nk}]^T \end{aligned} \quad (6)$$

where

$$\varphi_{ik}(\cdot) = u_k^i(t-1) \quad \text{for } i = 0, 1, 2, \dots, n$$

The error e_k is given by

$$e_k = y_k - W_k^T X_k \quad (7)$$

The parameter γ in Eq. (5) is the leakage factor and $0 < \gamma < 1$. It helps to avoid uncontrolled parameter drift in the algorithm which occurs for non-persistently exciting input X_k . The parameter μ is a time varying step size

¹The feed-forward controller $C(\cdot)$ is designed only to cause the plant $P(\cdot)$ track the output and not to stabilize it.

proportional to input vector X_k which helps to provide faster rate of convergence. The parameter $\delta > 0$ is used to avoid large step size when X_k becomes small. The detailed convergence and stability analysis of the algorithm is provided in [7]. The adapted U-model parameters $\omega_j(t)$ are then provided on-line to $C(\cdot)$ as represented by a dashed line in Fig. 1. The controller $C(\cdot)$ calculates $u(t)$ by a standard root solving algorithm such as Newton-Raphson method of Eq. (4). The evaluated $u(t)$ is then used to drive $P(\cdot)$ and $M(\cdot)$. Thus when $d(t)$ has been minimized, the inverse of $P(\cdot)$ is obtained, and $u(t)$ ultimately causes $P(\cdot)$ to follow the command input $U(t)$. The control action is feed-forward as there is no feedback signal. However, it exists only in the adaptation loop of the controller parameters.

4 Experimental setup and results

A thermal heating process typically consists of a blower, a heating grid, tube, and a temperature sensor. The purpose of this process is to heat the air flowing through the tube to a desired temperature level. Air drawn by a blower is driven past a heater grid and through a tube. A thermistor probe placed at a certain point along the tube is used to measure the temperature of the air. The function of the controller is to compare the measured air temperature with a desired value and generate a control signal that determines the amount of electrical power supplied to a heater mounted adjacent to the blower. The heating process is a nonlinear system. The main nonlinearities are due to the nonlinearity of the heating element and the lack of insulation (the heat transfer to the tube). The process is also characterized by inherent time delays. The setup of the implementation is shown in Fig. 2:

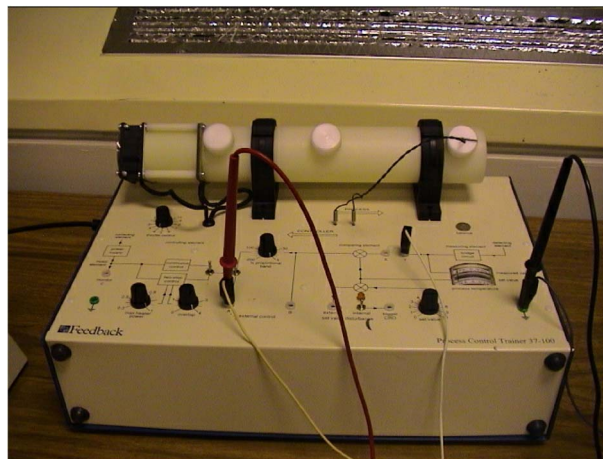


Fig. 2. Experimental setup of thermal heating process

A standard IBM PC-type Pentium III is used for the computation in real time. Data acquisition is accomplished by Advantech card PCI-1711 and the controller is implemented in Simulink real-time windows target environment. For the parameter identification third order U-model is utilized taken from Eq. (3) as:

$$y(t) = \omega_0(t) + \omega_1(t)u(t-1) + \omega_2(t)u^2(t-1) + \omega_3(t)u^3(t-1) \quad (8)$$

Based on the model in Eq. (8), the control law is evaluated by Newton-Raphson method of Eq. (4) as:

$$u_{q+1}(t-1) = u_q(t-1) - \eta \frac{y(t) - U(t)}{\omega_1(t) + 2\omega_2(t)u_q(t-1) + 3\omega_3(t)u_q^2(t-1)} \quad (9)$$

where $U(t)$ is treated as root solver and the subscript q is the iteration index. The control law formulation is general and simple. Here η is a learning rate parameter introduced to improve the adaptation. The value for η is taken 0.09 while the tab weights $\omega_j(t)$ are randomly initialization between 0 to 1. The learning rate for NLLMS is 0.6 while the leakage factor is 0.999999. The sampling time is 0.01 s. The results are shown in Fig. 3.

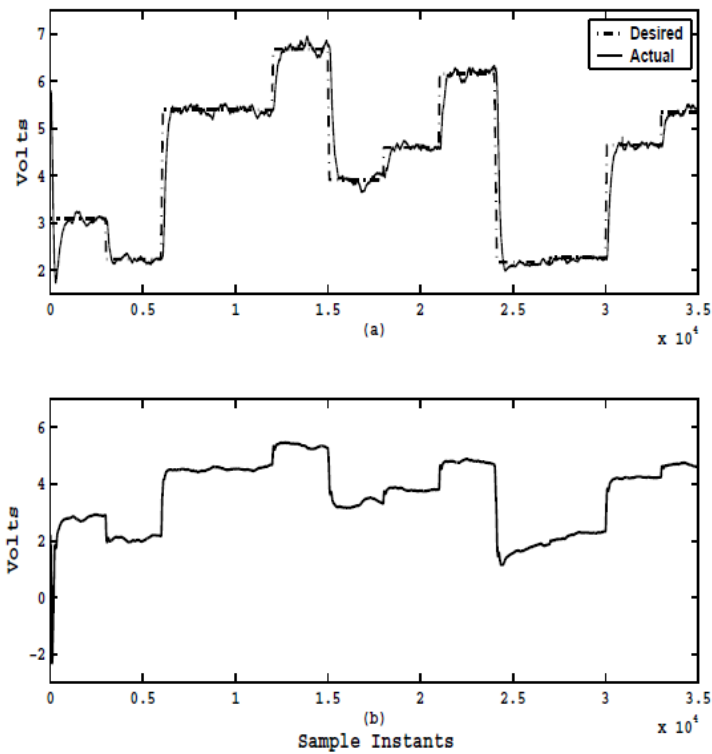


Fig. 3. (a) Desired and actual level (b) control signal

5 Conclusion

A novel feed-froward control scheme for unknown nonlinear dynamic plants was presented. The scheme was based on a control oriented model known as the U-model. The use of U-model reduced the computational complexity of nonlinear controller design that arises when using other modelling frame works such as NARMAX model. Based on this modelling framework the plant inverse was evaluated on-line by using Newton-Raphson method. The

implementation of U-model with the proposed AIC structure provided a simple and efficient method for control of unknown nonlinear dynamic plants. The proposed scheme was examined by controlling temperature of nonlinear heating process in real-time. The results indicated that the proposed scheme was able to control the nonlinear system adequately.

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