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Adaptive Observer Based Data-Driven Control for Nonlinear Discrete-Time Processes

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***Abstract*—In this paper, two adaptive observer-based strategies are proposed for control of nonlinear processes using input/output (I/O) data. In the two strategies, pseudo-partial derivative (PPD) parameter of compact form dynamic linearization and PPD vector of partial form dynamic linearization are all estimated by the adaptive observer, which are used to dynamically linearize a nonlinear system. The two proposed control algorithms are only based on the PPD parameter estimation derived online from the I/O data of the controlled system, and Lyapunov-based stability analysis is used to prove all signals of close-loop control system are bounded. A numerical example, a steam-water heat exchanger example and an experimental test show that the proposed control algorithm has a very reliable tracking ability and a satisfactory robustness to disturbances and process dynamics variations.**

***Note to Practitioners*–In actual industrial process, the dynamic behaviors is complex and nonlinear, and their mathematical models are often difficult to obtain. How to design the controller for unknown nonlinear systems using input/output (I/O) data has become one main focus of control researches. Therefore, in this paper, two adaptive observer-based data-driven control algorithms are proposed for a class of unknown nonlinear systems. Finally, the effectiveness of two control strategies are illustrated via simulation study and experimental test.**

***Index Terms*—Data-driven control, adaptive observer, pseudo-partial derivative, Lyapunov-based stability analysis, nonlinear discrete-time systems.**

I. Introduction

MODEL-based control techniques are usually implemented under the assumption of superior identification of process dynamics and their operational circumstances. However, these techniques cannot give satisfactory results when suffering poorly modeling [1-3]. This is often the case when dealing with complex, highly nonlinear natural dynamic processes. Although, adaptive technique based fuzzy logic and neural network have been intensively researched For nonlinear systems in the last two decades [4-8]. There are still no assurance of high convergence speed, the over-heating phenomenon, avoidance of local minima and so on; meanwhile, there are not general methods to choose the number of the fuzzy rule base and hidden units of common neural network.

The term *data-driven* was firstly proposed in computer science and has only recently entered the vocabulary of the control society. Because only the input/output (I/O) measurement data is used in data-driven controller design procedure. The modelling process, the unmodeled dynamics and the theoretical assumptions all disappear. So it has caught considerable attention in recent years [9-17]. There are a few data-driven control (DDC) methods as following: model-free adaptive control (MFAC)[9-10], virtual reference feedback tuning (VRFT)[11-12], iterative learning control (ILC)[13], lazy learning control (LLC) [14], unfalsified control (UC) methodology [15], dynamic programming method [16-17] and others [18-19].

As one of the data drive control methods, MFAC has been proposed and applied in several areas. Hou [9-10,20] has designed MFAC algorithm based on compact form dynamic linearization (CFDL), partial form dynamic linearization (PFDL), and full form dynamic linearization (FFDL) for single-input single-output (SISO), multi-input single-output (MISO), and multi-input multi-output (MIMO) systems. However, the MFAC is still developing. *How to prove the stability and convergence of the tracking problems* is one of the open problems in MFAC [20]. We all know, Lyapunov functional is widely used to analysis the stability of close-loop system [21].

In this paper, we focus on how to design data-driven controller based on Lyapunov method. Inspired by the work of dynamic linearization technique of Hou [5-6], we present two adaptive observer-based control strategies for nonlinear processes systems in which the pseudo-partial derivative (PPD) theory is used to dynamically linearize the nonlinear system. In order to achieve the time-varying PPD parameter estimation, based on discrete-time adaptive observer technique, a novel adaptive strategy for computing the PPD term is designed by using the Lyapunov method. A stability analysis is carried out to prove that, in the case of perfect parametrization of the CFDL and PFDL, the system is globally exponentially stable. Then, inverse control algorithm is used to design the data-driven controller via CFDL, and one-step-ahead weighted predictive control is used to design the controller via PFDL. The stability analysis for tracking errors of the proposed algorithms is provided. Last, the paper discusses the different

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parameter tuning, and uses simulations for a numerical plant, a steam-water heat exchanger process and experiments to show that the proposed control algorithm has a good tracking ability and a satisfactory robustness to disturbances and process dynamics variations.

The rest of this paper is organized as follows. In Section II, a brief descriptions of the CFDL and PFDL is given. In Section III, main results of adaptive observer based data-driven control via CFDL are proposed. Next main results of adaptive observer based data-driven control via PFDL are developed in Section IV. Simulation results are presented to show the effectiveness of the proposed technique in in Section V. Finally, some conclusions are made at end of this paper.

II. Data-driven modeling (dynamical linearization technique)

Consider discrete-time SISO nonlinear system represented in the following Nonlinear AutoRegressive with eXogenous input (NARX) model:

$$y(k+1)=f(y(k),\cdots,y(k-d_y),u(k),\cdots,u(k-d_u)) \tag{1}$$

where y, u are the system output and input, d_y, d_u are the unknown orders, and $f(\cdot)$ is an unknown nonlinear function.

The proposed novel data-driven control algorithm is designed with PPD technique. Here, we simply introduce the CFDL and PFDL. Details can see [5,7].

A. Compact Form Dynamic Linearization

The CFDL of the system (1) is based on following two necessary assumptions.

Assumption 1: The partial derivative of $f(\cdot)$ with respect to the control input $u(k)$ is continuous.

Assumption 2: The system (1) is generalized Lipschitz, that is, satisfying $\Delta y(k+1)\le C_1|\Delta u(k)|$, for $\forall k$ and $|\Delta u(k)|\neq 0$, where $\Delta y(k+1)=y(k+1)-y(k)$, and $\Delta u(k)=u(k)-u(k-1)$. and C_1 is a constant.

Theorem 1: For the nonlinear system (1), we assume that Assumptions 1 and 2 hold. There must exist a parameter $\phi(k)$, called PPD, system (1) can be transformed into the following CFDL description when $|\Delta u(k)|\neq 0$:

$$\Delta y(k+1)=\Delta u(k)\phi(k) \tag{2}$$

where $|\phi(k)|\le C_1$

Proof: See reference [5]. ∎

B. Partial Form Dynamic Linearization

The PFDL of the system (1) is based on following two necessary assumptions.

Assumption 3: The partial derivative of $f(\cdot)$ with respect to the control input $u(k),u(k-1)\cdots,u(k-L)$ are continuous. where L is a positive constant called control input length constant of linearization for the discrete-time nonlinear system (1).

Assumption 4: The system (1) is generalized Lipschitz, that is, satisfying $\Delta y(k+1)\le C_2\|\Delta U(k)\|$, for $\forall k$ and $\|\Delta U(k)\|\neq 0$, where $\Delta y(k+1)=y(k+1)-y(k)$, and $\Delta U(k)=[\Delta u(k),\cdots,\Delta u(k-L+1)]^T$, $\Delta u(k-i)=u(k-i)-u(k-i-1), i=0,\cdots,L-1$ and C_2 is a constant.

Theorem 2: For the nonlinear system (1), we assume that Assumptions 3 and 4 hold. There must exist a parameter vector $\Phi(k)$, called PPD vector, system (1) can be transformed into the following PFDL description when $\|\Delta U(k)\|\neq 0$:

$$\Delta y(k+1)=\Delta U^T(k)\Phi(k) \tag{3}$$

where $\Phi(k)=[\phi_1,\phi_2,\cdots,\phi_L]^T$, and $\|\Phi(k)\|\le C_2$

Proof: See reference [5]. ∎

The following works are based on basic assumption.

Assumption 5: For Theorem 1 and Theorem 2, the norm of the parameter $\Delta u(k)$ and vector $\Delta U(k)$ is uniformly bounded by constants $\Omega_1>0$ and $\Omega_2>0$, i.e., $|\Delta u(k)|\le\Omega_1$, and $\|\Delta U(k)\|\le\Omega_2$.

Notice that Assumption 5 can be satisfied for a wide class of functions $\Delta u(k)$ and $\Delta U(k)$, by assuming that the output $y(k)$ and the input $u(k)$ of the system (1) remains bounded.

III. Controller Design via Compact Form Dynamic Linearization

In this section, we will propose a novel data-driven control algorithm using the CFDL model. Main contributions in the following works include as: 1) A novel unknown PPD estimation algorithm; 2) Proposed a data-driven inverse control algorithm; 3) Lyapunov-based stability analysis.

A. Observer-Based PPD Parameter Identification

The proposed PPD parameter identification observer has the following structure

$$\hat{y}_c(k+1)=\hat{y}_c(k)+\Delta u(k)\hat{\phi}(k)+k_c e_c(k) \tag{4}$$

where $e_c(k)=y(k)-\hat{y}_c(k)$ is the output estimation error, $\hat{\phi}(k)$ represents an estimate of the PPD parameter, and the gain k_c is chosen such that $F_c=1-k_c$ in the unit circle.

Hence, in view of (2) and (4), the output estimation error dynamics is given by

$$e_c(k+1)=F_c e_c(k)+\Delta u(k)\tilde{\phi}(k) \tag{5}$$

where $\tilde{\phi}(k)=\phi(k)-\hat{\phi}(k)$ represents the PPD parameter estimation error.

The PPD term can be tactfully calculated through the estimation of ϕ. Namely, an adaptive update law for the parameters $\phi(k)$ can be chosen as

$$\hat{\phi}(k+1)=\hat{\phi}(k)+\Delta u(k)\Gamma_c(k)(e_c(k+1)-F_c e_c(k)) \tag{6}$$

The gain $\Gamma_c(k)$ is chosen as follows

$$\Gamma_c(k)=2\left(|\Delta u(k)|^2+\mu\right)^{-1}$$

where μ is a positive constant, hence, $\Gamma_c(k)$ is positive definite for all k. Notice that, by Assumption 5, $\Gamma_c(k)$ can be lower bounded as

$$|\Gamma_c(k)|\ge\frac{2}{\Omega_1^2+\mu}=\gamma_c>0$$

By taking into account (5) and (6), the estimation error dynamics can be written as

$$\begin{aligned} e_c(k+1) =& F_c e_c(k) + \Delta u(k)\tilde{\phi}(k) \\ \tilde{\phi}(k+1) =& H_c \tilde{\phi}(k) \end{aligned} \tag{7}$$

where H_c is given by

$$H_c = 1 - \Delta u^2(k)\Gamma_c(k)$$

The main property of estimate scheme is recapitulated in the following theorem.

Theorem 3: Under Assumption 5, the equilibrium $[e_c, \tilde{\phi}] = [0, 0]$ of the system (7) is globally uniformly stable. Furthermore, the estimation error $e_c(k)$ converges asymptotically to 0.

Proof: Consider the Lyapunov function

$$V(k) = P_c e_c^2(k) + \lambda_c \tilde{\phi}^2(k)$$

where λ_c, Q_c are positive constants and P_c is the solution by $P_c - F_c^2 P_c = Q_c$, the solution P_c exists and is positive definite. By taking into (7), we have

$$\begin{aligned} \Delta V(k+1) =& V(k+1) - V(k) \\ =& - Q_c e_c^2(k) + 2P_c F_c \Delta u(k) e_c(k)\tilde{\phi}(k) \\ & - \left[\lambda_c(1-H^2) - P_c \Delta u^2(k)\right]\tilde{\phi}^2(k) \\ =& - Q_c e_c^2(k) - \left[\mu\lambda_c \Gamma_c^2(k) - P_c\right]\eta^2(k) \\ & + 2P_c F_c e_c(k)\eta(k) \\ \leq& - Q_c e_c^2(k) - \left[\mu\lambda_c\gamma_c^2 - P_c\right]\eta^2(k) \\ & + 2P_c F_c e_c(k)\eta(k) \\ \leq& - c_1 e_c^2(k) - c_2\eta^2(k) \end{aligned}$$

where $\eta(k) = \Delta u(k)\tilde{\phi}(k)$, $c_1 = Q_c - \frac{1}{\varepsilon}$, $c_2 = \mu\lambda_c\gamma_c^2 - P_c - \varepsilon P_c^2 F_c^2$. Hence, $\Delta V(k+1) \leq 0$ provided that ε, Q_c and λ_c satisfy the following inequalities

$$Q_c > \frac{1}{\varepsilon}, \quad \mu\lambda_c\gamma_c^2 - P_c - \varepsilon P_c^2 F_c^2 > 0$$

Notice that $\Delta V(k)$ is negative definite in the variables $e_c(k)$, $\eta(k)$. Since $V(k)$ in a decreasing and non-negative function, it converges to a constant value $V_\infty \geq 0$, as $k \to \infty$, hence, $\Delta V(k) \to 0$. This implies that both $e_c(k)$ and $\tilde{\phi}(k)$ remain bounded for all k, and $\lim_{k\to\infty} e(k) = 0$. ■

B. Controller Design and Stability Analysis

Based on the observer (4), the data-driven inverse control law can be described as

$$\begin{aligned} & u(k) = u(k-1) + \frac{\hat{\phi}(k)(y^*(k+1) - \hat{y}_c(k) - k_c e_c(k))}{\hat{\phi}^2(k) + \alpha}, \\ & \qquad \text{for} \quad |\Delta u(k)| \leq \delta \\ & u(k) = u(k-1) + \delta \text{sign}(\Delta u(k)), \quad \text{for} \quad |\Delta u(k)| > \delta \end{aligned} \tag{8}$$

where $y^*(k)$ is reference trajectory. α and δ as given finite positive numbers. Notice that, in many practical systems, because their actuators cannot change too fast, the number δ can be jammy obtained.

Define observer tracking error $e_o(k) = y^*(k) - \hat{y}_c(k)$, thus

$$\begin{aligned} e_o(k+1) =& y^*(k+1) - \hat{y}_c(k+1) \\ =& y^*(k+1) - \hat{y}_c(k) - \Delta u(k)\hat{\phi}(k) - k_c e_c(k) \end{aligned} \tag{9}$$

The robustness of the stability and the performance for data-driven control law (8) are given in Theorem 4.

Theorem 4: For given $|y^*(k) - y^*(k-1)| \leq \Delta y^*$, using the data-driven control law (8), the solution of close-loop observer error system (9) is uniformly ultimately bounded (UUB) [22] for all k with ultimate bound $\lim_{k\to\infty} |e_o(k)| \leq \frac{a_2}{1-a_1}$.

where Δy^* is a given positive constant, $0 < s_0(k) \leq 1$,

$$\begin{aligned} a_1 &= 1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}, \\ a_2 &= \left(1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}\right)|\Delta y^* - k_c e_c(k)|. \end{aligned}$$

Proof: Define a variable $s_0(k)$ where $0 < s_0(k) \leq 1$ for all k. The control law (8) is equivalently expressed as

$$\Delta u(k) = \frac{y^*(k+1) - \hat{y}_c(k) - k_c e_c(k)}{\hat{\phi}^2(k) + \alpha} s_0(k)\hat{\phi}(k) \tag{10}$$

where

$$\begin{aligned} & s_0(k) = 1, && \text{for} \quad |\Delta u(k)| \leq \delta \\ & 0 < s_0(k) < 1, && \text{for} \quad |\Delta u(k)| > \delta \end{aligned}$$

Using (10), (9) becomes

$$\begin{aligned} |e_o(k+1)| =& \left(1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}\right) \\ & \times |\left(y^*(k+1) - \hat{y}_c(k) - k_c e_c(k)\right)| \\ =& \left(1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}\right) \\ & \times |\left(y^*(k+1) - y^*(k) + e_o(k) - k_c e_c(k)\right)| \\ \leq& \left(1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}\right)|e_o(k)| \\ & + \left(1 - s_0(k) + \frac{s_0(k)\alpha}{\hat{\phi}^2(k) + \alpha}\right)|\Delta y^* - k_c e_c(k)| \\ =& a_1|e_o(k)| + a_2 \end{aligned} \tag{11}$$

Choosing a Lyapunov function as $V(k) = |e_o(k)|$, from (11), one has

$$\Delta V(k+1) = |e_o(k+1)| - |e_o(k)| = (1 - a_1)V(k) + a_2$$

Since $0 \leq a_1 < 1$ and a_2 is bounded, according to the lemma in [22], using the control law (8), the results of close-loop observer system (9) are UUB for all k with ultimate bound $\lim_{k\to\infty} |e_o(k)| \leq \frac{a_2}{1-a_1}$. ■

Corollary 1: Under the controller (8), together with the observer (4), adaptive laws (6), we can guarantee that the system (1) tracking error $e(k) = y^*(k) - y(k)$ is UUB with ultimate bound $\lim_{k\to\infty} |e(k)| \leq \frac{a_2}{1-a_1}$.

Proof: Since

$$e(k) = e_o(k) - e_c(k) \tag{12}$$

Taking the absolute value and limiting on both sides of (12), we obtain

$$\begin{aligned}\lim_{k\to\infty}|e(k)| \leq &\lim_{k\to\infty}|e_o(k)| + \lim_{k\to\infty}|e_c(k)| \\ \leq &\frac{a_2}{1-a_1}\end{aligned} \tag{13}$$

So the tracking error $e(k)$ is UUB for all k with ultimate bound $\lim_{k\to\infty}|e(k)| \leq \frac{a_2}{1-a_1}$. ■

Remarks :

1) In order to make the parameter estimation law have a stronger capability in tracking time-varying parameter, a retune mechanism which in [7] should be considered as following

$$\begin{aligned}\hat{\phi}(k) =&\hat{\phi}(1), \\ &\text{if} \quad |\hat{\phi}(k)| \leq \epsilon \quad \text{or} \quad \text{sign}(\hat{\phi}(k)) \neq \text{sign}(\hat{\phi}(1))\end{aligned} \tag{14}$$

where where ϵ is a small positive constant and $\hat{\phi}(1)$ is the initial value of $\hat{\phi}(k)$.

2) If the reference trajectory $y^*(k) = \text{constant}$, we can obtain the $\Delta y^* = 0$, and from the Theorem 3, the $\lim_{k\to\infty} e_c(k) = 0$. Hence, the number $a_2 = 0$, we can simply obtained the result $\lim_{k\to\infty}|e(k)| = 0$.

IV. Controller Design via Partial Form Dynamic Linearization

In this case the focus is on PFDL, based on the PPD parameter vector estimation of adaptive observer which is similar as Section III(A), we propose a enhanced data-driven control algorithm.

A. Observer Design

The proposed PPD parameter identification observer has the following structure

$$\hat{y}_p(k+1) = \hat{y}_p(k) + \Delta U^T(k)\hat{\Phi}(k) + k_p e_p(k) \tag{15}$$

where $e_p(k) = y(k) - \hat{y}_p(k)$ is the output estimation error, $\hat{\Phi}(k)$ represents an estimate of the PPD parameter vector, and the gain k_p is chosen such that $F_p = 1 - k_p$ in the unit circle. And the adaptive update law for the parameters estimate $\Phi(k)$ can be chosen as

$$\hat{\Phi}(k+1) = \hat{\Phi}(k) + \Delta U(k)\Gamma_p(k)(e_p(k+1) - F_p e_p(k)) \tag{16}$$

The gain $\Gamma_p(k)$ is chosen as follows

$$\Gamma_p(k) = 2\left(\|\Delta U(k)\|^2 + \mu_1\right)^{-1}$$

where μ_1 is a positive constant, hence, $\Gamma_p(k)$ is positive definite for all k. Notice that, by virtue of Assumption 5, $\Gamma_p(k)$ can be lower bounded as

$$|\Gamma_p(k)| \geq \frac{2}{\Omega_2^2 + \mu_1} = \gamma_p > 0$$

Hence, in view of (3) and (15), the output estimation error dynamics is given by

$$e_p(k+1) = F_p e_p(k) + \Delta U^T(k)\tilde{\Phi}(k) \tag{17}$$

where $\tilde{\Phi}(k) = \Phi(k) - \hat{\Phi}(k)$ represents the PPD parameter estimation error of PFDL.

By taking into account (16) and (17), the estimation error dynamics can be written as

$$\begin{aligned}e_p(k+1) =&F_p e_p(k) + \Delta U^T(k)\tilde{\Phi}(k) \\ \tilde{\Phi}(k+1) =&H_p\tilde{\Phi}(k)\end{aligned} \tag{18}$$

where H_c is given by

$$H_p = I_L - \Delta U(k)\Gamma_p(k)\Delta U^T(k)$$

and I_L denotes the $(L \times L)$ identity matrix.

Theorem 5: Under Assumption 5, the equilibrium $[e_p, \tilde{\Phi}^T]^T = [0, \mathbf{0}_{L\times 1}^T]^T$ of the system (18) is globally uniformly stable. Furthermore, the estimation error $e_p(k)$ converges asymptotically to 0.

Proof: Consider the Lyapunov function

$$V(k) = P_p e_p^2(k) + \lambda_p\tilde{\Phi}^T(k)\tilde{\Phi}(k)$$

where λ_p, Q_p are positive constant and P_p is the solution by $P_p - F_p^2 P_p = Q_p$. By taking into (18), we have

$$\begin{aligned}\Delta V(k+1) =&V(k+1) - V(k) \\ &\leq -Q_p e_p^2(k) - \left[\mu_1\lambda_p\gamma_p^2 - P_p\right]\Theta^2(k) \\ &\quad + 2P_p F_p e_p(k)\Theta(k) \\ &\leq -c_3 e_p^2(k) - c_4\Theta^2(k)\end{aligned}$$

where $\Theta(k) = \Delta U^T(k)\tilde{\Phi}(k)$, $c_3 = Q_p - \frac{1}{\varsigma}$, $c_4 = \mu\lambda_p\gamma_p^2 - P_p - \varsigma P_p^2 F_p^2$. Hence, $\Delta V(k+1) \leq 0$ provided that ς, Q_p and λ_p satisfy the following inequalities

$$Q_p > \frac{1}{\varsigma}, \quad \mu\lambda_p\gamma_p^2 - P_p - \varsigma P_p^2 F_p^2 > 0$$

Notice that $\Delta V(k)$ is negative definite in the variables $e_p(k)$, $\Theta(k)$. Since $V(k)$ in a decreasing and non-negative function, it converges to a constant value $V_\infty \geq 0$, as $k \to \infty$, hence, $\Delta V(k) \to 0$. This implies that both $e_p(k)$ and $\tilde{\Phi}(k)$ remain bounded for all k, and $\lim_{k\to\infty} e_p(k) = 0$. ■

Remark 3: In order to make the parameter estimation law have a stronger capability in tracking time-varying parameters, a retune mechanism which in [5] should be considered as following

$$\hat{\phi}_1(k) =\hat{\phi}_1(1), \quad \text{if} \quad |\hat{\phi}_1(k)| \leq \epsilon \tag{19}$$

where where ϵ is a small positive constant and $\hat{\phi}_1(1)$ is the initial value of $\hat{\phi}_1(k)$.

B. Enhanced Controller Design

The control law can be achieved by minimizing the one-step-ahead weighted predictive control performance index

$$J = [y^*(k+1) - \hat{y}_p(k)]^2 + \lambda[\Delta u(k)]^2 \tag{20}$$

$\lambda(\lambda > 0)$ denotes the control effort weighting factor. Taking (15) into (20) and then minimizing it, we can achieve the following control law

$$\begin{aligned}u(k) = u(k-1) +& \frac{\hat{\phi}_1(k)(y^*(k+1) - \hat{y}_p(k) - k_p e_p(k))}{\hat{\phi}_1^2(k) + \lambda} \\ &- \frac{\hat{\phi}_1(k)\sum_{i=2}^{L}\hat{\phi}_i(k)\Delta u(k-i+1)}{\hat{\phi}_1^2(k) + \lambda}\end{aligned} \tag{21}$$

An adaptive modification item (AMI) [23] $\psi(k)$ is introduced to the control law (21). Then the control law can be rewritten as

$$\begin{aligned} u(k) = u(k-1) - \psi(k)\frac{\hat{\phi}_1(k)\sum_{i=2}^{L}\hat{\phi}_i(k)\Delta u(k-i+1)}{\hat{\phi}_1^2(k)+\lambda} \\ + \psi(k)\frac{\hat{\phi}_1(k)(y^*(k+1)-\hat{y}_p(k)-k_p e_p(k))}{\hat{\phi}_1^2(k)+\lambda} \end{aligned} \quad (22)$$

Theorem 6: There exists suitable $\psi(k)$ such that the observer tracking error $e_{\mathbf{o}}(k)$ will be to 0.

Proof: Define observer tracking error $e_{\mathbf{o}}(k) = y^*(k) - \hat{y}_p(k)$, thus

$$\begin{aligned} e_{\mathbf{o}}(k+1) =& y^*(k+1) - \hat{y}_p(k+1) \\ =& a_3\left(y^*(k+1) - \hat{y}_p(k) - k_p e_p(k)\right) \\ & - a_3\left(\sum_{i=2}^{L}\hat{\phi}_i(k)\Delta u(k-i+1)\right) \end{aligned} \quad (23)$$

Where

$$a_3 = 1 - \frac{\psi(k)\hat{\phi}_1^2(k)}{\hat{\phi}_1^2(k)+\lambda}$$

So, there exists suitable AMI as

$$\psi(k) = \frac{\hat{\phi}_1^2(k)+\lambda}{\hat{\phi}_1^2(k)}$$

which can make $e_{\mathbf{o}}(k+1) = 0$. ■

The AMI, which is time-varying parameter, and may be tuned for high tracking ability [23-24]. In most cases, $\psi(k)$ is chosen as 1 [24]. [23] gives a simple recursive efficient method, and in this paper we using the recursive efficient method of [23] for calculating the $\psi(k)$ in our simulations.

Corollary 2: Under the controller (22), together with the observer (15), adaptive laws (16), we can guarantee that the tracking error $e(k) = y^*(k) - y(k)$ is convergent.

Proof: The Prove is similar as Corollary 1. ■

Remark 4: We can also obtain the one-step-ahead control from the optimization of the cost function (20) by using the gradient descent optimizing technique [25], i.e.,

$$u(k) = u(k-1) - \frac{\varrho}{1+\varrho\sigma}e_{\mathbf{o}}(k+1)\frac{\partial e_{\mathbf{o}}(k+1)}{\partial u(k)} \quad (24)$$

where $\varrho > 0$ is the optimizing step. Considering the observer model (15). The sensitivity $\partial e_{\mathbf{o}}(k+1)/\partial u(k)$ can be derived from the

$$\frac{\partial e_{\mathbf{o}}(k+1)}{\partial u(k)} = -\hat{\phi}_1(k)$$

If the parameters satisfy $0 < \frac{\varrho}{1+\varrho\sigma}\sigma \leq 1$, the control algorithm given in (24) will be convergent. Suppose the Lyapunov function is defined as $V = e_{\mathbf{o}}^2(k+1) + \Delta e_{\mathbf{o}}^2(k+1)$, the sufficient condition for the stability of the one-step ahead data-driven control system is $\frac{\varrho}{1+\varrho\sigma} \leq \frac{1}{|C_2|^2}$.

V. Simulation and experimental results

In this section, simulation and experiments are shown to demonstrate the validity of the proposed data-driven control algorithmes. A nonlinear system and steam-water heat exchanger process simulations are conducted to test the algorithm effectiveness. The output tracking capability, load rejection capability, and the robustness to process dynamic changes are tested in this simulation. To demonstrate the real application, the proposed algorithm is also experimentally tested with a level control system.

A. Case study 1

The following SISO nonlinear process model is used in the simulation [26]:

$$y(k+1) = \sin[y(k)] + u(k)(5 + \cos[y(k)u(k)]) \quad (25)$$

Existing the disturbance in input channel which is described as

$$u(k) = u_c(k) + 0.01 * \sin(2\pi k/200)$$

The tracking trajectory is given as

$$\begin{aligned} y^*(k) = 0.6 + 0.2\,[&\sin(2\pi k/50) \\ &+ \sin(2\pi k/100) + \sin(2\pi k/150)] \end{aligned} \quad (26)$$

For the propose of comparison, the DDC-CFDL and DDC-PFDL are compared to the neural based inverse control (NIC) [27] approach with the disturbance of input.

1) Data-Driven Control based on CFDL: For the proposed control law, we choose the sampling time $T_s = 1$. The parameters of proposed control law in Section III are $k_c = 0.9$, $\mu = 0.1$, $\alpha = 0.01$, $\delta = 0.2$, $\epsilon = 10^{-10}$ and $\hat{\phi}(1) = 10$.

System responses are shown in Fig. 1 (A), which are included output signals of DDC-CFDL and NIC (i.e. Fig. 1 (A(1))), input signals (i.e. Fig. 1 (A(2))), PPD parameter estimation (i.e. Fig. 1 (A(3))) for the DDC-CFDL in case study 1. The simulations in Fig. 1 (A) show good tracking performance, and is not affected much by the increasing magnitude of the tracking trajectory (26). From Fig. 1 (A), the tracking error significantly decreases using the proposed DDC-CFDL in comparison to NIC. The proposed data driven controller can achieve a better performance in the presence of disturbance.

2) Data-Driven Control based on PFDL: The parameters of proposed control law in Section IV are $L = 3$, $k_p = 0.9$, $\mu_1 = 0.1$, $\lambda = 0.01$, $\epsilon = 10^{-10}$ and $\hat{\Phi}(1) = [3, 3, 3]^T$.

Fig. 1 (B(1-3)) shows that output signals of DDC-PFDL and NIC, input signals, and PPD parameter estimation of DDC-PFDL. It can be seen that the proposed DDC-PFDL can achieve a better performance in the presence of disturbance. This is because the DDC structures does not include a plant model, the controller is only from I/O data.

B. Case study 2

Heat exchangers are universal elements in the chemical and process industry. Temperature control is still a major task if the heat exchanger is operated over a broad scale. The nonlinear behavior depends strongly on the flow rates and on

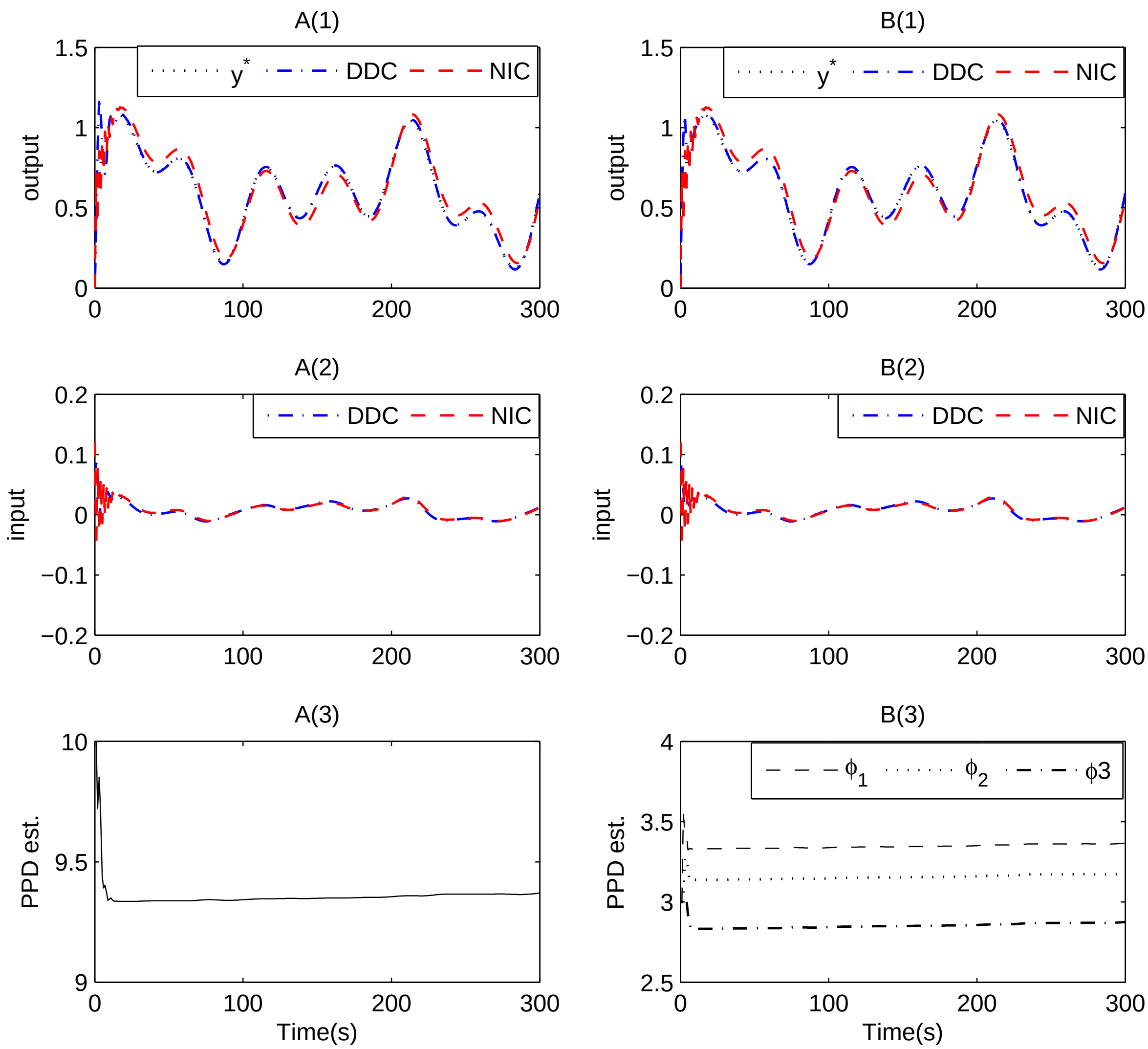

Fig. 1. (A) The signals of response for DDC-CFDL in case study 1. (B) The signals of response for DDC-PFDL in case study 1.

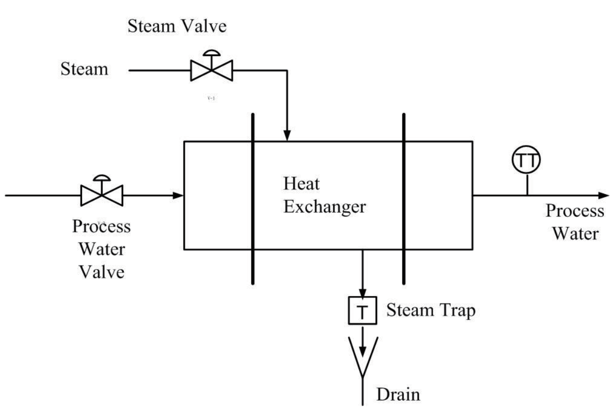

Fig. 2. Heat exchanger.

the temperatures of the media. In this section, a steam-water heat exchanger is considered. Equations of the steam-water heat exchanger dynamic, which represent a complex behavior. The experimental equipment is shown in Fig. 2. The steam condenses in the two-pass shell and tube heat exchanger, so raising the process water temperature. The steam flow rate and process water flow rate can be controlled by pneumatic control values. [28] describes the plant where the heat exchanger dynamic is expressed by a Hammerstein model (the nonlinear element follows linear block) and it is given by

$$G_H(z^{-1}) = \frac{0.207z^{-1} - 0.1764z^2}{1 - 1.608z^{-1} + 0.6385z^{-2}} \tag{27}$$

$$N(u) = -31.549u + 41.732u^2 - 24.201u^3 + 68.634u^4 \tag{28}$$

We choose the parameters of DDC-CFDL are $k_c = 0.9$, $\mu = 10$, $\alpha = 0.01$, $\delta = 0.2$, $\epsilon = 10^{-10}$ and $\hat{\phi}(1) = -50$. And the parameters of DDC-PFDL are chosen as $k_p = 0.9$,

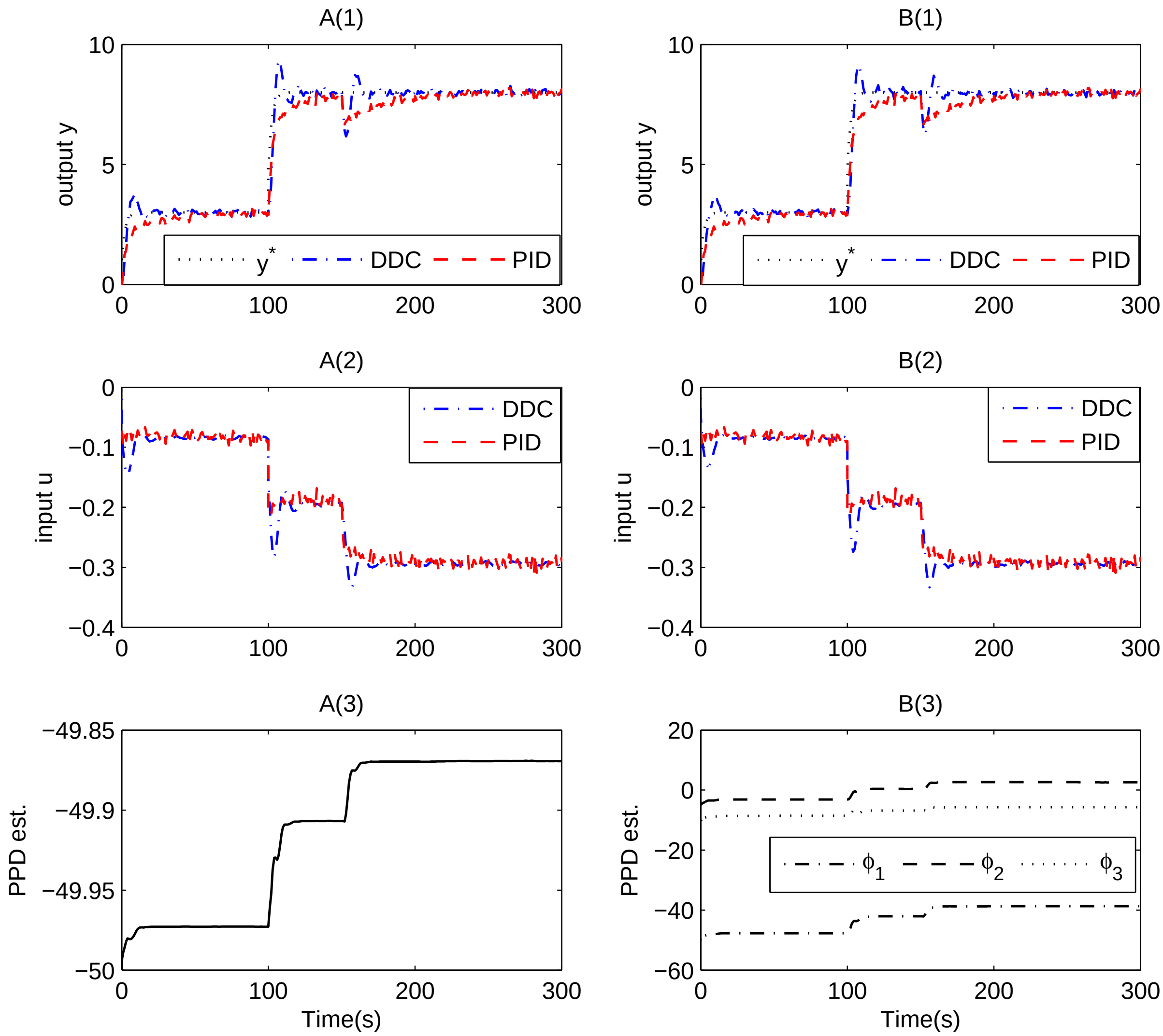

Fig. 3. (A) The signals of response for DDC-CFDL in case study 2. (B) The signals of response for DDC-PFDL in case study 2.

$\mu_1 = 0.1$, $\lambda = 0.01$, $\hat{\Phi}(1) = [-50, -15, -10]^T$.

The control simulations is based on measurement noise $0.005\mathrm{rand}(1)$ and the step disturbance 0.1 at 150s in input channel. The desired trajectories to be tracked are

$$y^* = \begin{cases} 3 & t < 100 \\ 8 & t \geq 100 \end{cases}$$

The simulation results of two proposed DDC are shown in Fig. 3. Fig. 3 (A(1)) and Fig. 3 (B(1)) give the DDC-CFDL and DDC-PFDL output response. The control signals of two control laws are shown in Fig. 3 (A(2)) and Fig. 3 (B(2)). Fig. 3 (A(3)) and Fig. 3 (B(3)) describe the PPD parameter estimations of by two data-driven controllers. These two simulations show that acceptable set-point tracking can be obtained with the proposed control algorithm for the nonlinear process. The results also show that the close-loop systems with two proposed DDC have stronger anti-interference ability than robust PID control method [29].

C. Experimental results

The proposed DDC-CFDL and DDC-PFDL methods were experimentally evaluated on a process control system (PCS). The PCS is made by FESTO company, which is built up by four working units (Level control, temperature control, pressure control, flow control). Each unit can work independently, and flexible connections with other units through hardware and software integration to constitute a complex system. Fig. 4 shows a photograph of this PCS, and the block diagram figure of level control unit is illustrated in Fig. 5.

Where the *SIMENS*® S7-300 (lower-computer) is used to collect data for field devices. The liquid level of tank (B102) is measured by ultrasonic liquid level sensor (LIC102). The control signal is constrained between 0 and 10 V for DC motor (P101).

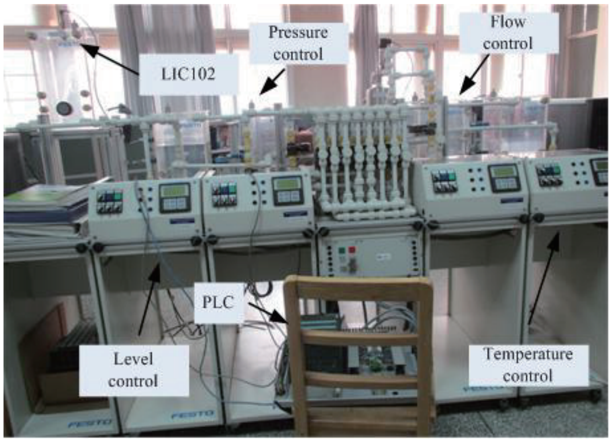

Fig. 4. PCS experimental device.

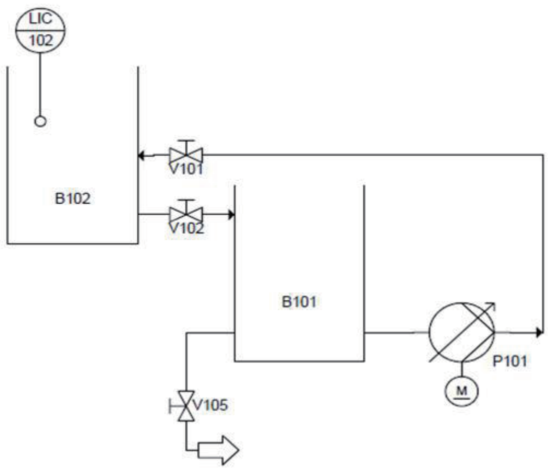

Fig. 5. Block diagram of level control unit.

The parameters of DDC-CFDL are chosen as $k_c = 0.9$, $\mu = 10$, $\alpha = 0.01$, $\delta = 0.2$, $\epsilon = 10^{-10}$ and $\hat{\phi}(1) = -500$. And the parameters of DDC-PFDL are chosen as $k_p = 0.9$, $\mu_1 = 0.1$, $\lambda = 0.01$, $\hat{\Phi}(1) = [-500, -170, -80]^T$. The experimental

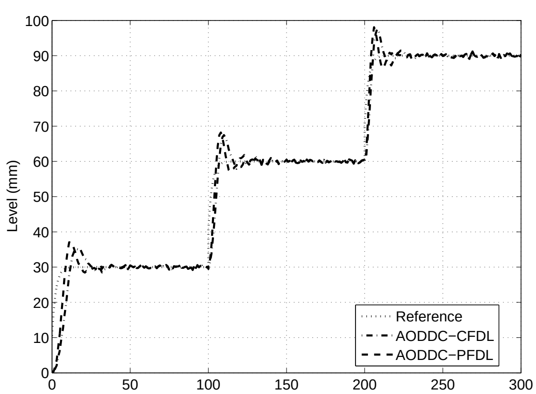

Fig. 6. Level response to the set-point changes.

result is shown in Fig. 6 for the set-point tracking control, and Fig. 7 gives the control responses to a disturbance produced by

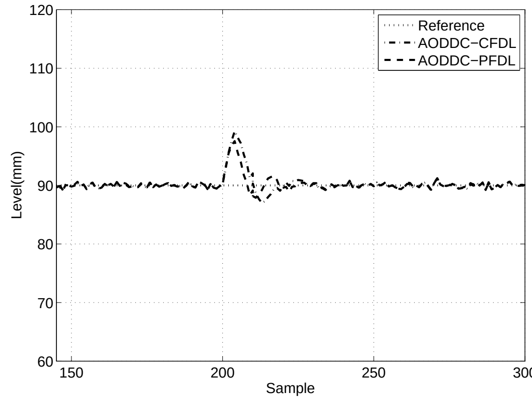

Fig. 7. Level response to disturbance.

pouring 3 L of water into the tank B102 at the 200th sample. These two experiments show that acceptable set-point tracking and disturbance rejection can be obtained with the proposed control algorithm for the nonlinear process.

VI. Conclusion

The PPD was used to dynamically linearize a nonlinear process, and aggregation was used to predict the PPD. To rely on dynamically linearize technology, we propose adaptive observer based two novel and effective data-driven control law for unknown nonlinear dynamic processes. The two control has the real-time implementation advantage of not requiring any iterative computation for determining the control input. And the Lyapunov-based stability analysis is introduces to the proposed control systems. The simulations and experiments show that the proposed control algorithms have good tracking capability, acceptable robustness to disturbances and process dynamics changes. It is believed that the proposed algorithm is a favorable control strategy for unknown nonlinear systems where realtime application is important.

Furthermore, the DDC for multi-input single-output (MISO), and multi-input multi-output (MIMO) systems will be studied in our further works.

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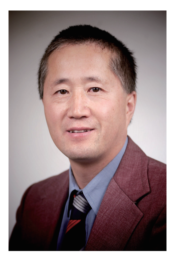

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