Letter

Data-Driven Adaptive PID Tracking Control of a Class of Nonlinear Systems

Tong Mu, Haibin Guo, *Member, IEEE*, Chuandong Bai, and Zhong-Hua Pang, *Senior Member, IEEE*

Dear Editor,

This letter investigates a low-complexity data-driven adaptive proportional-integral-derivative (APID) control scheme to address the output tracking problem of a class of nonlinear systems. First, the relationship between PID parameters is established to reduce the number of adjustable parameters to one. Then, based on the incremental triangular data model, a data-driven APID tracking control (DD-APIDTC) method is proposed to adjust only one controller parameter and one model parameter online, both of which have clear physical meaning. Subsequently, sufficient conditions are derived for the boundedness of the system tracking error. Finally, simulation results are given to illustrate the effectiveness of the proposed method.

Nowadays, the requirement for the tracking control performance of practical systems, especially unknown nonlinear systems, is increasing [1]. To simplify the analysis and design of nonlinear systems, they are usually transformed into linear forms by linear approximation at some operating points, such as three dynamic linearization data models at each operating point were established in [2], and an equivalent linearization design method for nonlinear controllers was discussed in [3]. However, the data model and controller in the above works are derived by Cauchy differential mean value theorem. Model or controller parameters are solely mathematical concepts without analytical expression and actual physical meaning, which potentially cause the inaccurate parameter estimation in practical applications. To solve this problem, an incremental triangular data model based on the system impulse response model was proposed in [4], while the controller does not make full use of historical tracking error information and the structure is not fixed.

PID control method is still preferred in most engineering applications, which requires suitable adaptive updating rules to adjust controller parameters in real time when system properties change. However, most existing adaptive updating rules highly depend on system knowledge. For some complex systems, especially nonlinear systems, accurate mathematical models are difficult to be established [5]. To solve the tracking control problem of nonlinear systems, several data-driven APID control schemes have been developed, such as database-driven APID control [6], learning-based APID control [7], and APID-like control [8]. However, in the aforementioned works, three APID control parameters are adjusted independently, which increases the complexity for tuning parameters. Although this problem is considered in [9], the design of the adaptive update rule still requires the system prior knowledge, which is difficult for nonlinear systems with unknown model. The above discussion motivates this study. The main contributions of this letter are summarized as follows. 1) A low-complexity APID controller is proposed by establishing a relationship between three adjustable parameters. 2) Inspired by [4], an online adaptive parameter tuning algorithm using more historical data of the system is presented. 3) A DD-APIDTC method is proposed to address the tracking control problem of nonlinear systems, and sufficient conditions for the boundedness of the tracking error are obtained.

Corresponding author: Zhong-Hua Pang.

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The authors are with the Key Laboratory of Fieldbus Technology and Automation of Beijing, North China University of Technology, Beijing 100144, China (e-mail: chmt@mail.ncut.edu.cn; haibin.guo@ncut.edu.cn; baichd_1975@ncut.edu.cn; zhonghua.pang@ia.ac.cn).

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Notations: $\mathbb{R}$ and $\mathbb{Z}^+$ are the sets of real numbers and positive integers, respectively. For the variable x_t, $\hat{x}_t$ denotes its estimate, and $\Delta x_t = x_t - x_{t-1}$.

Design of APID controller: Consider a class of discrete-time nonlinear systems

$$y_{t+1} = f(y_t, y_{t-1}, \ldots, y_{t-n_y}, u_t, u_{t-1}, \ldots, u_{t-n_u}) \tag{1}$$

where $y_t \in \mathbb{R}$ and $u_t \in \mathbb{R}$ are the system output and input, respectively, $n_y \in \mathbb{Z}^+$ and $n_u \in \mathbb{Z}^+$ are the unknown orders of y_t and u_t, respectively, and $f(\cdot)$ is an unknown nonlinear function. Assume that the partial derivative $\frac{\partial f(\cdot)}{\partial u_t}$ is continuous, and system (1) satisfies the generalized Lipschitz condition.

For a given reference signal $y_t^{\rm ref} \in \mathbb{R}$, the tracking error is defined as $e_t = y_t^{\rm ref} - y_t$. Then, an APID controller is designed as

$$\Delta u_t = k_{{\rm p},t}(e_t - e_{t-1}) + k_{{\rm i},t} e_t + k_{{\rm d},t}(e_t - 2e_{t-1} + e_{t-2}) \tag{2}$$

where $k_{{\rm p},t}$, $k_{{\rm i},t}$ and $k_{{\rm d},t}$ are the controller parameters to be adjusted. Obviously, if these parameters are adjusted independently, the parameter tuning process would be quite complex and time-consuming. To solve this problem, the relationship between $k_{{\rm p},t}$, $k_{{\rm i},t}$ and $k_{{\rm d},t}$ is built by introducing a coefficient $\alpha > 0$, that is

$$k_{{\rm p},t} = 2\alpha k_{{\rm d},t}, \quad k_{{\rm i},t} = \alpha^2 k_{{\rm d},t} \tag{3}$$

based on which, APID control law (2) is reexpressed as

$$\Delta u_t = k_{{\rm d},t}\mathcal{E}_t \tag{4}$$

where $\mathcal{E}_t = (\alpha+1)^2 e_t - (2\alpha+2)e_{t-1} + e_{t-2}$, and $k_{{\rm d},t}$ is bounded, i.e., $0 < \underline{d}_1 \le k_{{\rm d},t} \le \bar{d}_1$ with two positive constants $\underline{d}_1$ and $\bar{d}_1$.

Remark 1: According to the parameter relationship in (3), it can be obtained that the characteristic equation of APID controller (4) is $(z^{-1} - (\alpha+1))^2 = 0$, and the characteristic root $z = \frac{1}{\alpha+1}$ is within the unit circle when $\alpha > 0$, which allows that only $k_{{\rm d},t}$ needs to be tuned in APID controller (4). In addition, it is noted that APID controller (4) can also be designed based on $k_{{\rm p},t}$ or $k_{{\rm i},t}$ instead of $k_{{\rm d},t}$ by redefining (3).

Adaptive parameter tuning rule: In order to obtain $k_{{\rm d},t}$, the following performance index function is considered:

$$J(k_{{\rm d},t}) = (y_{t+1}^{\rm ref} - y_{t+1})^2 + \lambda_t (k_{{\rm d},t} - k_{{\rm d},t-1})^2 \tag{5}$$

where $\lambda_t > 0$ is a time-varying weighting factor. Since the system output y_{t+1} is unknown at time t, the dynamic linearization technology is employed to predict the system output. According to [4], nonlinear system (1) can be equivalently transformed into the following incremental triangular data model:

$$\Delta y_{t+1} = h_t \omega_t \tag{6}$$

where h_t satisfies $\underline{h} \le |h_t| \le \bar{h}$ with constants $\underline{h}$ and $\bar{h}$, and

$$\omega_t = \sum_{i=1}^{m} \frac{i}{m} \Delta u_{t-i+1} + \sum_{j=m+1}^{N} \frac{N-j}{N-m} \Delta u_{t-j+1} \tag{7}$$

with constant integers $N \ge 2$ and $0 < m < N$. For the physical meanings of h_t, N, and m as well as the selection of N and m, please refer to [4].

Substituting (6) and (7) into (5) and minimizing cost function (5) with respect to $k_{{\rm d},t}$ yields

$$k_{{\rm d},t} = \frac{\lambda_t}{\gamma_t} k_{{\rm d},t-1} + \frac{(y_{t+1}^{\rm ref} - y_t - \zeta_t h_t) h_t \frac{1}{m}\mathcal{E}_t}{\gamma_t} \tag{8}$$

where $\gamma_t = \lambda_t + h_t^2 \frac{1}{m^2}\mathcal{E}_t^2$, and $\zeta_t = \sum_{i=2}^{m} \frac{i}{m}\Delta u_{t+1-i} + \sum_{j=m+1}^{N} \frac{N-j}{N-m} \times \Delta u_{t+1-j}$. To estimate h_t, the following parameter estimation algorithm is used [4]:

$$\hat{h}_t = \hat{h}_{t-1} + \frac{\omega_{t-1}}{\mu + \omega_{t-1}^2}(\Delta y_t - \hat{h}_{t-1}\omega_{t-1}) \tag{9}$$

where $\mu > 0$ is an estimation weighting factor. The corresponding reset algorithm is adopted to prevent $\hat{h}_t$ from being too small or its sign being opposite, i.e.,

$$\hat{h}_t = \hat{h}_0, \text{ if } |\hat{h}_t| \le \sigma \text{ or } \mathrm{sign}(\hat{h}_t) \ne \mathrm{sign}(\hat{h}_0) \tag{10}$$

where σ is a small positive constant.

The DD-APIDTC method: Combining (4) and (8)−(10), the overall DD-APIDTC method is formed as

$$\begin{cases} \hat{h}_t = \hat{h}_{t-1} + \dfrac{\omega_{t-1}}{\mu + \omega_{t-1}^2}(\Delta y_t - \hat{h}_{t-1}\omega_{t-1}) \\ \hat{h}_t = \hat{h}_0, \quad \text{if } |\hat{h}_t| \le \sigma \text{ or } \mathrm{sign}(\hat{h}_t) \ne \mathrm{sign}(\hat{h}_0) \\ k_{\mathrm{d},t} = \dfrac{\lambda_t}{\tilde{\gamma}_t} k_{\mathrm{d},t-1} + \dfrac{(y_{t+1}^{\mathrm{ref}} - y_t - \zeta_t \hat{h}_t)\hat{h}_t \frac{1}{m}\mathcal{E}_t}{\tilde{\gamma}_t} \\ \Delta u_t = k_{\mathrm{d},t}\mathcal{E}_t \end{cases} \tag{11}$$

where $\tilde{\gamma}_t = \lambda_t + \hat{h}_t^2 \frac{1}{m^2}\mathcal{E}_t^2$. The parameter estimate $\hat{h}_t$ satisfies $\underline{h}_1 \le |\hat{h}_t| \le \bar{h}_1$, where $\underline{h}_1$ and $\bar{h}_1$ are positive constants.

Remark 2: It can be seen from (11) that the proposed DD-APIDTC method is a pure data-driven control method. Furthermore, only one controller parameter $k_{\mathrm{d},t}$ is required to be adjusted in APID controller (4), which simplifies the controller structure and reduces the complexity of parameter adjustment. Compared with [4], the controller (4) uses more historical tracking error information and has a fixed structure. Different from [9], the DD-APIDTC method does not require the system prior knowledge and an additional fixed controller gain, which can better ensure the control effect when the system properties change, such as the time-varying structure and time-varying parameters.

Convergence analysis: For the convenience of analysis, the reference signal is set as $y_t^{\mathrm{ref}} = y^{\mathrm{ref}}$, where y^{ref} is a constant. Before giving the analysis results, two reasonable assumptions are listed here.

Assumption 1: The increment of the historical control input is bounded, i.e., $|\Delta u_t| \le \rho$ for $t \le 0$, where $\rho > 0$ is a constant.

Assumption 2: The sign of h_t is to be known and unchanged.

Without loss of generality, consider that $\bar{h} \ge h_t \ge \underline{h} > 0$, and thus $\hat{h}_t \ge \underline{h}_1 > 0$ by using (10).

Theorem 1: The closed-loop DD-APIDTC system guarantees that the output tracking error is bounded, if there exist λ_t and α satisfying

$$\lambda_t \ge \mathcal{A} > 0 \tag{12}$$

$$\frac{1}{m}\max\{\bar{h}_1, \bar{h}\}\bar{d}_1(\alpha+1)^2 < 1 \tag{13}$$

$$\underline{d}_1\underline{h}(\alpha^2 - 2) > 0 \tag{14}$$

where $\mathcal{A} \triangleq \frac{(\hat{h}_t - \bar{h})\hat{h}_t \frac{1}{m^2}\mathcal{E}_t^2}{\frac{1}{m}\bar{h}\bar{d}_1(\alpha+1)^2 - 1}$.

Proof: From (6), the tracking error is derived as

$$e_{t+1} = e_t - h_t \frac{1}{m}\Delta u_t - h_t\zeta_t. \tag{15}$$

Then, according to (11), one has

$$\Delta u_t = q(\lambda_t)e_t - (2\alpha+2)p(\lambda_t)e_{t-1} + p(\lambda_t)e_{t-2} - l(\lambda_t)\zeta_t \tag{16}$$

where $q(\lambda_t) = \frac{\hat{h}_t \frac{1}{m}\mathcal{E}_t^2 + \lambda_t k_{\mathrm{d},t-1}(\alpha+1)^2}{\tilde{\gamma}_t}$, $p(\lambda_t) = \frac{\lambda_t k_{\mathrm{d},t-1}}{\tilde{\gamma}_t}$, and $l(\lambda_t) = \frac{\hat{h}_t^2 \frac{1}{m}\mathcal{E}_t^2}{\tilde{\gamma}_t}$. Substituting (16) into (15) yields

$$e_{t+1} = \beta(\lambda_t)e_t + \theta(\lambda_t)(2\alpha+2)e_{t-1} - \theta(\lambda_t)e_{t-2} + \Theta_t \tag{17}$$

where $\beta(\lambda_t) = 1 - g(\lambda_t)$, $\Theta_t = (\hat{h}_t l_1(\lambda_t) - h_t)\zeta_t$, and

$$g(\lambda_t) = \frac{h_t \frac{1}{m}(\hat{h}_t \frac{1}{m}\mathcal{E}_t^2 + \lambda_t k_{\mathrm{d},t-1}(\alpha+1)^2)}{\tilde{\gamma}_t}$$

$$\theta(\lambda_t) = \frac{h_t \frac{1}{m}(\lambda_t k_{\mathrm{d},t-1})}{\tilde{\gamma}_t}, l_1(\lambda_t) = \frac{\hat{h}_t \frac{1}{m}\mathcal{E}_t^2}{\tilde{\gamma}_t} h_t \frac{1}{m}.$$

Then, taking the absolute value on both sides of (17) gives

$$|e_{t+1}| \le \Gamma(\lambda_t)\max\{|e_t|, |e_{t-1}|, |e_{t-2}|\} + |\Theta_t| \tag{18}$$

where $\Gamma(\lambda_t) = |\beta(\lambda_t)| + |\theta(\lambda_t)(2\alpha+2)| + |-\theta(\lambda_t)|$.

The partial derivative of $g(\lambda_t)$ with respect to λ_t is derived as

$$\frac{\partial g(\lambda_t)}{\partial \lambda_t} = \frac{\frac{1}{m^2}h_t\hat{h}_t\mathcal{E}_t^2}{(\lambda_t + \frac{1}{m^2}(\hat{h}_t\mathcal{E}_t)^2)^2}(\frac{1}{m}\hat{h}_t k_{\mathrm{d},t-1}(\alpha+1)^2 - 1). \tag{19}$$

From (13), one has $\frac{1}{m}\hat{h}(t)k_{\mathrm{d},t-1}(\alpha+1)^2 - 1 \le \frac{1}{m}\bar{h}_1\bar{d}_1(\alpha+1)^2 - 1 \le \max\{\bar{h}_1, \bar{h}\}\frac{1}{m}\bar{d}_1(\alpha+1)^2 - 1 \le 0$, which means that (19) is less or equal to 0, i.e., $g(\lambda_t)$ is a non-increasing function. Thus, one obtains $g(\lambda_t) \ge \lim_{\lambda_t\to\infty} g(\lambda_t) = \frac{1}{m}h_t k_{\mathrm{d},t-1}(\alpha+1)^2 \ge \frac{1}{m}\underline{d}_1\underline{h}(\alpha+1)^2 > 0$.

Next, combining (12) and (13) gives $\lambda_t(\frac{1}{m}\bar{h}\bar{d}_1(\alpha+1)^2 - 1) \le (\hat{h}_t - \bar{h})\hat{h}_t\frac{1}{m^2}\mathcal{E}_t^2$, which further yields

$$\frac{\lambda_t \frac{1}{m}\bar{h}\bar{d}_1(\alpha+1)^2 + \frac{1}{m^2}\bar{h}\hat{h}_t\mathcal{E}_t^2}{\lambda_t + \frac{1}{m^2}\hat{h}_t^2\mathcal{E}_t^2} \le 1$$

i.e., $g(\lambda_t) \le 1$. Therefore, $0 \le \beta(\lambda_t) = 1 - g(\lambda_t) < 1$ holds. Then, with the definition of $\Gamma(\lambda_t)$, it is derived that

$$\begin{aligned}\Gamma(\lambda_t) &= 1 - g(\lambda_t) + \theta(\lambda_t)(2\alpha+3) \\ &= 1 - s(\lambda_t)\end{aligned} \tag{20}$$

where $s(\lambda_t) = \frac{h_t \frac{1}{m}(\hat{h}_t \frac{1}{m}\mathcal{E}_t^2 + \lambda_t k_{\mathrm{d},t-1}(\alpha^2-2))}{\tilde{\gamma}_t}$.

According to the definition of $g(\lambda_t)$ and $s(\lambda_t)$, one has

$$s(\lambda_t) < \frac{h_t \frac{1}{m}(\hat{h}_t \frac{1}{m}\mathcal{E}_t^2 + \lambda_t k_{\mathrm{d},t-1}(\alpha+1)^2)}{\tilde{\gamma}_t} = g(\lambda_t) \le 1.$$

Taking the partial derivative of $s(\lambda_t)$ with respect to λ_t, one yields

$$\frac{\partial s(\lambda_t)}{\partial \lambda_t} = \frac{\frac{1}{m^2}h_t\hat{h}_t\mathcal{E}_t^2}{(\lambda_t + \frac{1}{m^2}(\hat{h}_t\mathcal{E}_t)^2)^2}(\frac{1}{m}\hat{h}_t k_{\mathrm{d},t-1}(\alpha^2-2) - 1). \tag{21}$$

According to (13), one has $\frac{1}{m}\hat{h}_t k_{\mathrm{d},t-1}(\alpha^2-2) < \frac{1}{m}\max\{\bar{h}_1, \bar{h}\}\bar{d}_1(\alpha+1)^2 < 1$, which means that (21) is less to 0, i.e., $s(\lambda_t)$ is a non-increasing function. Therefore, according to (14), there exist a small positive constant ϵ such that $s(\lambda_t) \ge \lim_{\lambda_t\to\infty} s(\lambda_t) = \frac{1}{m}h_t k_{\mathrm{d},t-1}(\alpha^2 - 2) \ge \frac{1}{m}\underline{d}_1\underline{h}(\alpha^2-2) \ge \epsilon > 0$, i.e., $0 < \Gamma(\lambda_t) \le 1 - \epsilon$.

Then, from the definition of $g(\lambda_t)$, it is derived that

$$0 < g(\lambda_t) = l_1(\lambda_t) + \frac{h_t \frac{1}{m}\lambda_t k_{\mathrm{d},t-1}(\alpha+1)^2}{\tilde{\gamma}_t} \le 1$$

i.e., $0 < l_1(\lambda_t) < 1$. According to Assumption 1, one has

$$\begin{aligned}|\Theta_t| &= |\hat{h}_t l_1(\lambda_t) - h_t||\zeta_t| \\ &\le (|\hat{h}_t l_1(\lambda_t)| + |h_t|)|\sum_{i=2}^{m}\frac{i}{m}\Delta u_{t+1-i} + \sum_{j=m+1}^{N}\frac{N-j}{N-m}\Delta u_{t+1-j}| \\ &< (\bar{h}_1 + \bar{h})(N-2)\rho.\end{aligned}$$

From (18), it is obtained that

$$\begin{aligned}|e_{t+1}| &< \Gamma(\lambda_t)\max\{|e_t|, |e_{t-1}|, |e_{t-2}|\} + \iota \\ &< \Gamma(\lambda_t)^2\max\{|e_{t-1}|, |e_{t-2}|, \ldots, |e_{t-5}|\} + \Gamma(\lambda_t)\iota + \iota \\ &\vdots \\ &< \Gamma(\lambda_t)^{t+1}|e_0| + \xi\end{aligned} \tag{22}$$

where $\iota = (\bar{h}_1 + \bar{h})(N-2)\rho$, $\xi = \frac{\iota}{\epsilon}$, and $e_t = 0$ for $t < 0$. Since e_0 is bounded, from (22), one has $\lim_{t\to\infty}|e(t)| < \xi$. ■

Numerical simulation: The methods in [2]–[4] and [9] are used as comparison with the proposed DD-APIDTC method. Consider a structure-varying and parameter-varying nonlinear system

$$y_{t+1}=\begin{cases}\dfrac{y_{t-1}}{1+\varphi_t y_{t-1}^2}+u_{t-1}^3, & t<350\\ 0.1\varphi_t y_{t-1}+0.2(y_{t-2}+u_{t-1})+0.18u_{t-2}, & 350\le t\le 600.\end{cases}$$

where $\varphi_t=1+0.5\sin(\frac{t\pi}{200})$. The reference signal is set as $y_{t+1}^{\mathrm{ref}}=0.5\mathrm{sign}(\sin(\frac{t\pi}{100}))$. The parameter settings for the five control methods are shown in Table 1, where $I=[1\ \ 1\ \ 1]^T$. For the method in [9], the core function is designed as $\Upsilon_t=1+|e_t|$. For more details about these parameters, please refer to [2]–[4] and [9].

Table 1. Parameter Settings

Control schemes	Parameters
DD-APIDTC	$m=2$, $N=5$, $\hat{h}_0=1$, $\lambda_t=30$, $\alpha=1.5$, $k_{\mathrm{d},0}=0$
Method in [2]	$L_y=2$, $L_u=1$, $\mu=1$, $\eta=1$, $\hat{\boldsymbol{\phi}}_{\mathrm{f},L_y,L_u}(0)=0.1I$, $\rho=1.5I$, $\lambda=1.5$
Method in [3]	$L_e=3$, $\eta=1$, $\hat{\psi}(1)=-0.6I$, $\lambda_t=50$
Method in [4]	$m=2$, $N=5$, $\hat{h}_0=1$, $\mu=1$, $\lambda=1$
Method in [9]	$\beta=1$, $\sigma_0=0.1$, $\sigma_1=0.1$, $\delta=1$, $k_{P0}=0.15$, $k_{I0}=0.2$, $k_{D0}=0.2$

The simulation results are given in Fig. 1, and the performance indices are shown in Table 2, where the integral absolute error (IAE) is $\sum_{t=200}^{600}|e_t|$ and the integrated time and absolute error (ITAE) is $\sum_{t=200}^{600}t|e_t|$. It can be seen from Fig. 1 that, when $t<350$, the DD-APIDTC method has the minimum overshoot under almost the same response time, and when $t\ge 350$, the response time of the DD-APIDTC method is the shortest. Meanwhile, Table 2 shows that the DD-APIDTC method has the smallest tracking error.

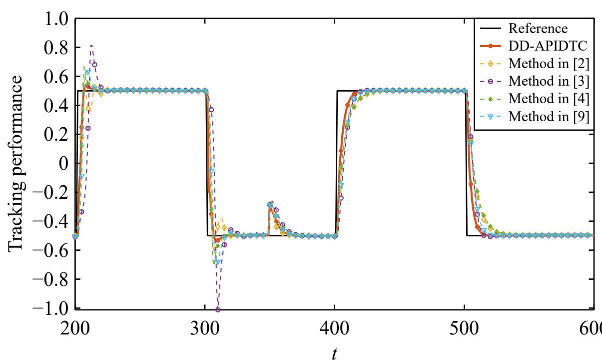

Fig. 1. Tracking performance under different methods.

Table 2. Performance Indices

Control schemes	IAE	ITAE
DD-APIDTC	13.7485	5072.8
Method in [2]	21.3983	8250.5
Method in [3]	30.1603	10283
Method in [4]	22.4849	8755.4
Method in [9]	22.0856	8105.9

Conclusion: This letter has proposed a DD-APIDTC method for the tracking control problem of a class of discrete-time nonlinear systems. The relationship between the three adjustable parameters in the APID controller has been established to simplify the controller structure. Then, based on the incremental triangular data model, an adaptive parameter tuning algorithm has been presented, where only one controller parameter and one model parameter are estimated online. In addition, the sufficient conditions for the boundedness of the tracking error have been obtained. Finally, the comparative simulation results have been given to verify the effectiveness and superiority of the proposed method.

It is well known that the integration of communication networks and control systems has become a hot topic in recent years, and thus communication constraints and cyber attacks will be addressed in our future work by extending the proposed method to networked nonlinear systems [10] and networked multi-agent systems [11].

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