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Practice article

Model-free adaptive integral terminal sliding mode predictive control for a class of discrete-time nonlinear systems ☆

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HIGHLIGHTS

- The proposed control approach is easy to implement because it merely uses the input and output data model of the system.
- A new model-free adaptive digital integral terminal sliding mode predictive control scheme without depending on any information of mathemati model.

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ABSTRACT

In this paper, a new model-free adaptive digital integral terminal sliding mode predictive contro scheme is proposed for a class of nonlinear discrete-time systems with disturbances. The characteristi of the proposed control approach is easy to be implemented because it merely adopts the input an output data model of the system based on compact form dynamic linearization (CFDL) data-drive technique, while the technique of perturbation estimation is applied to estimate the disturbanc term of the system. Moreover, by means of combining model predictive control and CFDL digita integral terminal sliding mode control (CFDL-DITSMC), the CFDL digital integral terminal sliding mod predictive control (CFDL-DITSMPC) method is proposed, which can further improve the trackin accuracy and disturbance rejection performance in comparison with the CFDL model-free adaptiv control, neural network quasi-sliding mode control and the CFDL-DITSMC scheme. Meanwhile, th stability of the proposed approach is guaranteed by theoretical analysis, and the effectiveness of th proposed method is also illustrated by numerical simulations and the experiment on the two-tan water level control system.

1. Introduction

In recent years, due to the continuous improvement of the control precision requirements, the control problem of nonlinear discrete time systems with perturbation and uncertainties has received increasing attention. Sliding mode control (SMC), as a nonlinear control strategy, is easy to be implemented and robust in the presence of interference, and has been successfully adopted in a large variety of areas [1,2]. However, the fine characteristics of continuous-time control systems disappear in the discrete-time control systems when the control sampling time increases. To solve the problem, in [3] the idea of discrete-time slidin mode control (DSMC), which has gradually received attention, i presented.

So far, numerous approaches have displayed the DSM schemes on various papers [4,5]. The existing literature has il lustrate that SMC with a conventional proportional type of slid ing function is able to possess a worse control performanc than the integral one [6,7]. Based on a sliding mode state ob server, the integral sliding function was used to design the con troller, and the control method can be easily applied to a micro /nanopositioning piezostage [8]. These methods mentioned abov require the model of the plant, that is to say, the control tech niques based on the model are usually implemented under th assumption concerning excellent understanding of process dy namics and their operational environment. However, it is actuall extremely difficult to obtain an accurate mathematical model.

As we know, the typical modern control methods ordinaril include adaptive control [9], model predictive control (MPC) [10 Backstepping control [11], and so on. Since the performanc

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valuation, stability analysis, controller designing, etc., are all de- endent on the assumptions, structure, and dynamics imposed on he mathematical model of the controlled process, it is also called nodel based control theory. At present, data-driven has been pplied to decision-making, fault diagnosis, and fault-tolerant ontrol, etc. In [12,13], a model-free adaptive control (MFAC) nethod based on the compact form dynamic linearization (CFDL) ata-driven modeling is proposed, when controller design and he closed-loop system analysis only used the measured input nd output data of the control system, without any model dy- amics involved. In practical industries, more than 500 scholars ook the MFAC approach to solve a variety of control issues, uch as the PWM control system [14,15], liquid-level control ystems [16–18], controller design for wind turbines and solar ower generation [19–21]. The literature [22] has first intro- uced the model-free adaptive sliding model control about the ombination of MFAC with DSMC. However, it fails to take the ffects of disturbance and system uncertainty into account. Based n [22], a neural network adaptive quasi-sliding mode control aw (NN-QSMC) based on CFDL is proposed in [23], in which radial basis function neural network (RBFNN) is used to es- imate the uncertainty and disturbance of the control system. ubsequently, many scholars have combined DSMC and MFAC o solve practical problems. By combining MFAC and the sliding node exponential reaching law, a speed controller for all the oints of the robot is developed to implement the target speed racking [24,25]. A method that combines advantages of SMC and IFAC is put forward for a pressure control system [26]. The com- ination of second-order SMC with MFAC has been adopted in the hree-tank level control system [27]. A model-free adaptive inte- ral SMC method with control input saturation is presented for utonomous four-wheeled mobile vehicle parking systems [28].

Recently, the literature [29] has employed the MPC to present digital integral terminal sliding mode predictive control DITSMPC) algorithm. However, combining the method of ITSMPC and CFDL has not been realized before, and how to yield n improved performance through combining them together is nknown. In this work, a CFDL-DITSMPC scheme designed for class of nonlinear discrete-time system with disturbances is roposed.

The main contribution of this paper is to propose a new CFDL- ITSMPC scheme without depending on any information of the nathematic model, which utilizes the CFDL technique and the echnique of perturbation estimation. Numerical simulation and xperimental verification show that the CFDL-DITSMPC algorithm much better than CPDL-MFAC, NN-QSMC and CFDL-DITSMC chemes in reducing the tracking error and disturbance rejection erformance. In the next section, a class of nonlinear systems and otations is introduced. The design procedure of CFDL-DITSMC nd CFDL-DITSMPC algorithms is explained in details in Sec- ions 3 and 4. Numerical simulation examples and experimental nvestigation are shown in Section 5, to explain the different erformances of the control system. Section 6 has given a brief ummary of the research approach.

. Problem formulation

The proposed control algorithm is designed based on CFDL echnique. Therefore, we first simply introduce the equivalent FDL data model with a concept called pseudo partial derivative PPD) for single input and single output (SISO) discrete-time onlinear system in this section. Details of the CFDL can be found n [12,13,16].

A SISO discrete-time nonlinear system is described as

$$ {}_m(k+1) = f\left(y(k), y(k-1), y\left(k-n_y\right), u(k), u(k-1), \ldots, u(k-n_u)\right) + f_p(k) \tag{1}$$

where $y_m(k)$ and $u(k)$ are output and input of the system, respectively; n_y and n_u are the unknown positive integers; $f_p(k)$ represents the bounded disturbances with $\left|f_p(k)\right| \leq D$, $D > 0$. $f(\cdot)$ stands for the discrete-time nonlinear system $y(k+1)$ as in

$$y_m(k+1) = y(k+1) + f_p(k) \tag{2}$$

Assumption 1. System (1) is controllable and observable, that is, if the desired signal $y_r(k+1)$ is bounded, then, the control input signal $u(k)$ is bounded, and $y_m(k+1)$ can track the desired signal $y_r(k+1)$.

Assumption 2. The partial derivative of $f(\cdot)$ with respect to control input $u(k)$ is continuous.

Assumption 3. The nonlinear system (1) is generalized Lipschitz, that is, $|\Delta y_m(k+1)| \leq b\,|\Delta u(k)|$under the condition of any k and $|\Delta u(k)| \neq 0$,where b>0, $\Delta y_m(k+1) = y_m(k+1) - y_m(k)$, and $\Delta u(k) = u(k) - u(k-1)$.

Remark 1. Assumption 1 is a basic requirement for the system to be controlled. To control such a system is impossible if Assumption 1 is not satisfied. Assumption 2 is satisfied for a general nonlinear system. Assumption 3 imposes an upper bound limitation on $\Delta y_m(k+1)$, which is a common condition in many nonlinear systems.

Lemma 1. *If $f(\cdot)$ satisfies Assumptions 1 and 2, when $|\Delta u(k)| \neq 0$, $\phi(k)$ called the PPD definitely exists. The CFDL data model can be described as*

$$\Delta y(k+1) = \phi(k)\,\Delta u(k) \tag{3}$$

where $|\phi(k)| \leq b$ is bounded for constant k at any time.

Rewrite (3) as

$$y(k+1) = y(k) + \phi(k)\,\Delta u(k) \tag{4}$$

From (2) and (4), we have

$$\Delta y_m(k+1) = \Delta y(k+1) + \Delta f_p(k) \tag{5}$$

where $\Delta y_m(k+1) = y_m(k+1) - y_m(k)$, $\Delta y(k+1) = y(k+1) - y(k)$, and $\Delta f_p(k) = f_p(k) - f_p(k-1)$.

Considering (3), then (5) can be further written as

$$y_m(k+1) = y_m(k) + \phi(k)\,\Delta u(k) + \Delta f_p(k) \tag{6}$$

Let $\phi(k) = \vartheta(k) + \delta$, and then it follows

$$y_m(k+1) = y_m(k) + (\vartheta(k) + \delta)\,\Delta u(k) + \Delta f_p(k) \tag{7}$$

where δ is the nonnegative constant.

Remark 2. It should be mentioned that the value of $\phi(k)$ in (3) may not be consistent with the variation range of $\phi(k)$, or in other words, $\phi(k)$ may satisfy

$$\max\left|\frac{\phi(k) - \phi(k-1)}{h}\right| \leq \bar{\varepsilon} \tag{8}$$

where $\bar{\varepsilon}$ is a positive constant and h represents the sampling interval. Therefore, $\phi(k)$ can be divided into the variable term $\vartheta(k)$ and the constant term δ. It is notable that $\phi(k)$ may be extremely small at some sampling times, and then the parameter δ is selected to ensure that$\phi(k)$ is maintained at an appropriate range.

3. CFDL-DITSMC design

The design process of the CFDL-DITSMC scheme is described in this section. First, the disturbance is estimated by adopting the technique of perturbation estimation. Then, a model free adaptive controller is obtained based on the CFDL data model and the DITSMC scheme. The stability of the proposed control method is also proved.

3.1. Disturbance estimation

The disturbance term $\Delta f_p(k)$ of the nonlinear system (6) can be estimated as

$$\Delta \hat{f}_p(k) = \Delta f_p(k-1) = y_m(k) - y_m(k-1) - \phi(k-1)\,\Delta u(k-1) \tag{9}$$

Then (6) can be written as

$$y_m(k+1) = y_m(k) + \phi(k)\,\Delta u(k) + \Delta \hat{f}_p(k) - \Delta \tilde{f}_p(k) \tag{10}$$

where $\Delta \tilde{f}_p(k) = \Delta \hat{f}_p(k) - \Delta f_p(k)$ is the disturbance estimation error, and we have

$$\begin{aligned} \Delta \tilde{f}_p(k) &= \Delta f_p(k-1) - \Delta f_p(k) \\ &= ((y_m(k) - y_m(k-1)) - (y_m(k+1) - y_m(k)) \\ &\quad - \phi(k-1)\,\Delta u(k-1) + \phi(k)\,\Delta u(k)) \end{aligned} \tag{11}$$

From Assumption 1 and Lemma 1, we know that $y_m(k)$, $u(k)$, and $\phi(k)$ are bounded. Thus, we can assume that $\Delta \tilde{f}_p(k)$ is bounded.

3.2. PPD estimation

Define $\hat{\phi}(k) = \hat{\vartheta}(k) + \delta$, and then the index function given in [13] for the unknown PPD estimation is used in this paper as

$$\begin{aligned} J\left(\hat{\phi}(k)\right) &= \left| y(k) - y(k-1) - \hat{\phi}(k)\,\Delta u(k-1) \right|^2 \\ &\quad + \mu \left| \hat{\phi}(k) - \hat{\phi}(k-1) \right|^2 \end{aligned} \tag{12}$$

where $\hat{\phi}(k)$ is the estimation value of $\phi(k)$. Using $\partial J / \partial \hat{\phi}(k) = 0$, we have

$$\begin{aligned} \hat{\phi}(k) &= \hat{\phi}(k-1) + \frac{\eta \Delta u(k-1)}{\mu + \Delta u(k-1)^2} \\ &\quad \times \left[\Delta y_m(k) - \Delta \hat{f}_p(k) - \hat{\phi}(k-1)\,\Delta u(k-1) \right] \end{aligned} \tag{13}$$

$$\hat{\vartheta}(k) = \hat{\vartheta}(1), \text{ if } \left|\hat{\vartheta}(k)\right| \le \varepsilon \text{or } |\Delta u(k-1)| \le \varepsilon \tag{14}$$

where $\mu > 0$; $\eta \in (0, 1]$; ε is a significantly small positive constant; the nonnegative constant $\hat{\vartheta}(1)$ is the initial value of $\hat{\vartheta}(k)$.

Then, (10) can be further written as

$$y_m(k+1) = y_m(k) + \left(\hat{\vartheta}(k) + \delta\right) \Delta u(k) + \Delta \hat{f}_p(k) - \Delta \tilde{f}_p(k) \tag{15}$$

where $\hat{\vartheta}(k)$ is the estimation value of $\vartheta(k)$,which can be obtained by Eq. (13).

Remark 3. In order to ensure the feasibility of the adaptive law (13), the choice of μ should be less than the value of $|\Delta u(k)|$.

Remark 4. The updating law (13) is designed merely by input and output measurement data of the controlled system, without any relations with model structural and dynamics information of the controlled system.

Remark 5. For the parameter estimation algorithm (13) hav stronger ability in tracking time-varying parameter, a reset mech anism has been given in (14). In addition, Eq. (14) also has bee utilized in stability analysis.

3.3. Design of the CFDL-DITSMC scheme

Define the tracking error as

$$e(k) = y_m(k) - y_r(k) \tag{16}$$

where $y_m(k)$ is the system output signal and $y_r(k)$ is the bounde desired input signal.

Define the PI type of the discrete terminal sliding function a follows [29]

$$s(k) = \lambda_1 e(k) + \lambda_2 E(k-1) \tag{17}$$

where $\lambda_1 > 0$ and $\lambda_2 > 0$, and the integral error item is

$$E(k) = \sum_{i=0}^{k} e_i^{\alpha} = E(k-1) + e_k^{\alpha} \tag{18}$$

where $0 < \alpha < 1$,which is the ratio of two odd numbers.

The CFDL-DITSMC control strategy can be derived from th discrete reaching law as follows

$$\Delta s(k) = s(k+1) - s(k) = 0 \tag{19}$$

From (19), the following equations can be obtained

$$s(k+1) = s(k) \tag{20}$$

$$\Rightarrow \lambda_1 e(k+1) + \lambda_2 E(k) = s(k) \tag{21}$$

$$\Rightarrow \lambda_1 (y_m(k+1) - y_r(k+1)) + \lambda_2 E(k) = s(k) \tag{22}$$

Substituting (15) into (22) yields

$$\begin{aligned} s(k) = \lambda_1 \Big[& y_m(k) + \left(\hat{\vartheta}(k) + \delta\right) \Delta u(k) \\ & + \Delta \hat{f}_p(k) - \Delta \tilde{f}_p(k) - y_r(k+1) \Big] + \lambda_2 E(k) \end{aligned} \tag{23}$$

The equivalent control $\Delta u^{eq}(k)$ can be obtained by Eq. (23) i the disturbance estimation error $\Delta \tilde{f}_p(k)$ is not taken into accoun

$$\begin{aligned} \Delta u^{eq}(k) = \frac{1}{\left(\hat{\vartheta}(k) + \delta\right)} \Big(& \lambda_1^{-1} s(k) - \lambda_1^{-1} \lambda_2 E(k) \\ & - \Delta \hat{f}_p(k) + y_r(k+1) - y_m(k) \Big) \end{aligned} \tag{24}$$

The implementation of the equivalent controller in (24) re quires a future reference position $y_r(k+1)$. In practice, the desire trajectory is usually predefined in the control system, so $y_r(k+1$ is known in (24).

It is worth noticing that the control law (24) can be obtaine by assuming that $\Delta \tilde{f}_p(k)$ is accurately estimated, i.e., $\Delta \tilde{f}_p(k) = ($ However, $\Delta \tilde{f}_p(k) \neq 0$. To guarantee the robustness of $\Delta u^{eq}(k$ consider a switching control action as follows

$$\Delta u^{sw}(k) = \frac{-\lambda_s}{\left(\hat{\vartheta}(k) + \delta\right)} \operatorname{sign}(s(k)) \tag{25}$$

where sign $(\cdot)$ denotes the signum function; λ_s satisfies the fol lowing condition

$$\lambda_s > \left| \Delta \tilde{f}_p(k) \right| \tag{26}$$

where $\Delta \tilde{f}_p(k)$ is described by (11). The control action of $\Delta u^{sw}(k$ is to tolerate the error of disturbance estimation so that the fina CFDL-DITSMC control law is shown as follows:

$$\Delta u(k) = \Delta u^{eq}(k) + \Delta u^{sw}(k) \tag{27}$$

That is

$$\Delta u(k)=\frac{1}{\left(\hat{\vartheta}(k)+\delta\right)}\left[\lambda_1^{-1}s(k)-\lambda_1^{-1}\lambda_2 E(k)-\Delta\hat{f}_p(k)\right.\\ \left.+y_r(k+1)-y_m(k)-\lambda_s \mathrm{sgn}(s(k))\right] \tag{28}$$

.4. Stability analysis

heorem 1. *The nonlinear system (1), satisfying Assumptions 1–3, controlled by the CFDL-DITSMC algorithms (13), (14), and (28), nd the desired signal $y_r(k+1)$ is bounded, and then the estimation alue of $\hat{\phi}(k)$ is bounded.*

roof. When $\left|\hat{\vartheta}(k)\right|\leq\varepsilon$, the reset algorithm (14) ensures that (k) is bounded.

When $\left|\hat{\vartheta}(k)\right|>\varepsilon$, subtracting $\phi(k)$ on both sides of (13) yields

$$\widetilde{\phi}(k)=\Delta\phi(k)+\left(1-\frac{\eta\Delta u(k-1)^2}{\mu+\Delta u(k-1)^2}\right)\widetilde{\phi}(k-1) \tag{29}$$

where $\widetilde{\phi}(k)=\phi(k)-\hat{\phi}(k)$, $\Delta\phi(k)=\phi(k)-\phi(k-1)$.

From Lemma 1, b is a positive constant and $|\phi(k)|\leq b$, it is bvious that

$$\left|\widetilde{\phi}(k)\right|<\left|\left(1-\frac{\eta\Delta u(k-1)^2}{\mu+\Delta u(k-1)^2}\right)\right|\left|\widetilde{\phi}(k-1)\right|+2b \tag{30}$$

Since $\mu>0$ and $\eta\in(0,1]$, then

$$\Delta u(k-1)^2<\Delta u(k-1)^2<\mu+\Delta u(k-1)^2 \tag{31}$$

Therefore, there is a positive constant $d\in(0,1]$, which leads o

$$<1-\frac{\eta\Delta u(k-1)^2}{\mu+\Delta u(k-1)^2}\leq d<1 \tag{32}$$

Hence

$$\begin{aligned}\left|\widetilde{\phi}(k)\right| &\leq d\left|\widetilde{\phi}(k-1)\right|+2b\\ &\leq d^2\left|\widetilde{\phi}(k-2)\right|+2db+2b\\ &\leq\cdots\leq d^k\left|\widetilde{\phi}(0)\right|+\frac{2b\left(1-d^k\right)}{1-d}\end{aligned} \tag{33}$$

In view of (33), $\widetilde{\phi}(k)$ is bounded. In this case, $\hat{\phi}(k)$ is bounded.

heorem 2. *Assuming that Assumptions 1–3 are held for the system 1), if the controller (28) with (26) is employed, and the time-varying arameters $\Delta\hat{f}_p(k)$ and $\hat{\phi}(k)$ can be updated by (9), (13) and (14), he quasi-sliding mode will achieve convergence in a finite number f steps.*

roof. From (14), the sliding mode function can be expressed as

$$s(k+1)=\lambda_1 e(k+1)+\lambda_2 E(k) \tag{34}$$

Substituting (16) into (34) and noting (15) as well as (28) gives

$$\begin{aligned}s(k+1)&=\lambda_1\left(y_m(k+1)-y_r(k+1)\right)+\lambda_2 E(k)\\ &=\lambda_1\left[y_m(k)+\left(\hat{\vartheta}(k)+\delta\right)\Delta u(k)+\Delta f_p(k)\right.\\ &\quad\left.-y_r(k+1)\right]+\lambda_2 E(k)\\ &=\lambda_1\left[\lambda_1^{-1}s(k)-\lambda_1^{-1}\lambda_2 E(k)+\Delta f_p(k)-\Delta f_p(k-1)\right.\\ &\quad\left.-\lambda_s\mathrm{sgn}(s(k))\right]+\lambda_2 E(k)\\ &=s(k)+\lambda_1\left(\Delta f_p(k)-\Delta f_p(k-1)\right)-\lambda_1\lambda_s\mathrm{sgn}(s(k))\end{aligned} \tag{35}$$

Substituting (11) into (35) yields

$$s(k+1)-s(k)=-\lambda_1\lambda_s\mathrm{sgn}(s(k))-\lambda_1\Delta\widetilde{f}_p(k) \tag{36}$$

From (26), we have

$$\lambda_s>\Delta\widetilde{f}_p(k)>-\lambda_s \tag{37}$$

Hence, when $s(k)$>0, from (36) and (37), the following equation can be obtained

$$\begin{aligned}&s(k+1)-s(k)=-\lambda_1\lambda_s-\lambda_1\Delta\widetilde{f}_p(k)\\ &\Rightarrow -2\lambda_1\lambda_s<s(k+1)-s(k)<0\end{aligned} \tag{38}$$

When $s(k)$<0, we have

$$\begin{aligned}&s(k+1)-s(k)=\lambda_1\lambda_s-\lambda_1\Delta\widetilde{f}_p(k)\\ &\Rightarrow 0<s(k+1)-s(k)<2\lambda_1\lambda_s\end{aligned} \tag{39}$$

In view of (38) and (39), then we can get

$$|s(k+1)-s(k)|<2\lambda_1\lambda_s \tag{40}$$

$$|s(k+1)|<|s(k)| \tag{41}$$

Eq. (41) satisfies the existing conditions of the discrete sliding mode [30]

$$\begin{aligned}&[s(k+1)-s(k)]\,\mathrm{sgn}(s(k))<0\\ &[s(k+1)+s(k)]\,\mathrm{sgn}(s(k))>0\end{aligned} \tag{42}$$

Thus, $s(k)$ is monotonically decreased, the quasi-sliding mode state will be reached in a limited number of steps, or in other words, the control system is stable and the tracking error converges to zero neighborhoods.

Remark 6. The chattering phenomenon may occur due to the sign function in (28). Therefore, in order to reduce the chattering phenomenon, the saturation function (43) is employed in the control law (28) to replace the sign function

$$\mathrm{sat}(k)=\begin{cases}\mathrm{sign}(s(k)), & \text{if } |s(k)|>\Delta\\ s(k)/\Delta, & \text{if } |s(k)|<\Delta\end{cases} \tag{43}$$

where $\Delta>0$, and the parameter Δ is usually tuned to make a trade-off between robustness of the controller and the chattering effect.

4. CFDL-DITSMPC design

In this section, a new strategy known as CFDL-DITSMPC for further improving the control system's tracking accuracy is developed.

4.1. The CFDL-DITSMPC scheme

A control action $\Delta u^{mp}(k)$ is generated by the MPC to drive the output of the system to the sliding surface. In view of (27), the total control action of CFDL-DITSMPC is

$$\Delta u^{sm}(k)=\Delta u(k)+\Delta u^{mp}(k) \tag{44}$$

Substituting the control algorithm (44) into (34) gets

$$\begin{aligned}s(k+1)&=\lambda_1\left(y_m(k+1)-y_r(k+1)\right)+\lambda_2 E(k)\\ &=\lambda_1\left[y_m(k)+\left(\hat{\vartheta}(k)+\delta\right)\Delta u^{sm}(k)+\Delta f_p(k)\right.\\ &\quad\left.-y_r(k+1)\right]+\lambda_2 E(k)\\ &=\lambda_1\left[\lambda_1^{-1}s(k)-\lambda_1^{-1}\lambda_2 E(k)+\Delta f_p(k)-\Delta f_p(k-1)\right.\\ &\quad\left.-\lambda_s\mathrm{sat}(s(k))+\left(\hat{\vartheta}(k)+\delta\right)\Delta u^{mp}(k)\right]+\lambda_2 E(k)\\ &=s(k)+\lambda_1\left(\hat{\vartheta}(k)+\delta\right)\Delta u^{mp}(k)-\lambda_1\Delta\widetilde{f}_p(k)\\ &\quad-\lambda_1\lambda_s\mathrm{sat}(s(k))\end{aligned} \tag{45}$$

From (45), we can obtain the N-step forward sliding mode function

$$\begin{aligned} s(k+N) = s(k) + \lambda_1 \Big[\left(\hat{\vartheta}(k)+\delta\right) \Delta u^{mp}(k) + \left(\hat{\vartheta}(k+1)+\delta\right) \\ * \Delta u^{mp}(k+1) + \cdots \\ + \left(\hat{\vartheta}(k+N-1)+\delta\right) \Delta u^{mp}(k+N-1) \Big] \\ -\lambda_1 \left[\Delta\widetilde{f}_p(k) + \Delta\widetilde{f}_p(k+1) + \cdots + \Delta\widetilde{f}_p(k+N-1)\right] \\ -\lambda_1\lambda_s \left[\mathrm{sat}(s(k)) + \mathrm{sat}(s(k+1)) + \cdots \\ + \mathrm{sat}(s(k+N-1))\right] \end{aligned} \tag{46}$$

where N is the number of the predictive horizon, let

$$S(k) = \left[\ s(k+1)\, s(k+2) \cdots s(k+N)\ \right]^T \tag{47}$$

$$U(k-1) = \left[\ \Delta u^{mp}(k)\, \Delta u^{mp}(k+1) \cdots \Delta u^{mp}(k+N-1)\ \right]^T \tag{48}$$

$$F(k-1) = \left[\Delta\widetilde{f}_p(k)\, \Delta\widetilde{f}_p(k+1) \cdots \Delta\widetilde{f}_p(k+N-1)\right]^T \tag{49}$$

$$T(k-1) = \left[\mathrm{sat}(s(k))\, \mathrm{sat}(s(k+1)) \cdots \mathrm{sat}(s(k+N-1))\right]^T \tag{50}$$

$$\Phi(k) = \begin{bmatrix} \hat{\vartheta}(k)+\delta & 0 & \cdots & 0 \\ \hat{\vartheta}(k)+\delta & \hat{\vartheta}(k+1)+\delta & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ \hat{\vartheta}(k)+\delta & \hat{\vartheta}(k+1)+\delta & \cdots & \hat{\vartheta}(k+N-1)+\delta \end{bmatrix} \tag{51}$$

Then rewrite (46) as

$$S(k) = \Lambda s(k) + \Phi U(k-1) - \Gamma F(k-1) - \mathrm{K}T(k-1) \tag{52}$$

where Λ represents the identity matrix; Γ and K are lower triangular matrices consisting of λ_1 and $\lambda_1\lambda_s$, respectively.

Define the performance function as follows

$$J = S^T(k) S(k) + \omega U^T(k-1) U(k-1) \tag{53}$$

where the value of ω determines the magnitude of the MPC control action. The smaller ω is, the greater the control action is, and vice versa.

Substituting (52) into (53), under the following optimization condition [31]

$$\frac{\partial J}{\partial U(k-1)} = 0 \tag{54}$$

Yields

$$\begin{aligned} U(k-1) = -\left(\Phi^T\Phi + \omega I\right)^{-1} \Phi^T \left(\Lambda s(k) \\ - \Gamma F(k-1) - \mathrm{K}T(k-1)\right) \end{aligned} \tag{55}$$

Due to the future disturbance value $F(k-1)$, the saturation function value $T(k-1)$ and the PPD matrix $\Phi(k)$ are unknown, and they are estimated as

$$\hat{F}(k-1) = \left[\Delta\widetilde{f}_p(k-1)\, \Delta\widetilde{f}_p(k-1) \cdots \Delta\widetilde{f}_p(k-1)\right]^T \tag{56}$$

$$\hat{T}(k-1) = \left[\mathrm{sat}(s(k))\, \mathrm{sat}(s(k)) \cdots \mathrm{sat}(s(k))\right]^T \tag{57}$$

$$\hat{\Phi}(k) = \begin{bmatrix} \hat{\vartheta}(k)+\delta & 0 & \cdots & 0 \\ \hat{\vartheta}(k)+\delta & \hat{\vartheta}(k)+\delta & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ \hat{\vartheta}(k)+\delta & \hat{\vartheta}(k)+\delta & \cdots & \hat{\vartheta}(k)+\delta \end{bmatrix} \tag{58}$$

In view of (55), the MPC control action for the k time is obtained as

$$\begin{aligned} \Delta u^{mp}(k) \\ = -\mathrm{X}\left(\hat{\Phi}^T\hat{\Phi} + \omega I\right)^{-1} \hat{\Phi}^T \left(\Lambda s(k) - \Gamma\hat{F}(k-1) - \mathrm{K}\hat{T}(k-1)\right) \end{aligned} \tag{59}$$

where $\mathrm{X} = \left[\ \lambda_1^{-1} 0 \cdots 0\ \right]$.

Therefore, substituting (24) and (59) into (44), then (44) can be expressed as

$$\begin{aligned} \Delta u^{sm}(k) = \frac{1}{\left(\hat{\vartheta}(k)+\delta\right)} \Big[\lambda_1^{-1} s(k) - \lambda_1^{-1}\lambda_2 E(k) - \Delta\hat{f}_p(k) \\ + y_r(k+1) - y_m(k)\Big] - \mathrm{X}\left(\Phi^T\Phi + \omega I\right)^{-1} \Phi^T \Big(\Lambda s(k) \\ - \Gamma\hat{F}(k-1) - \mathrm{K}\hat{T}(k-1)\Big) \end{aligned} \tag{60}$$

4.2. Stability analysis

Theorem 3. *The nonlinear system (1), satisfying Assumptions 1–3, is controlled by the CFDL-DITSMPC scheme (60), and the desired signal $y_r(k+1)$ is bounded. Then, the quasi-sliding mode will achieve convergence within a limited number of steps, and $e(k)$ is bounded.*

Proof. The proof of boundedness of $\hat{\phi}(k)$ is the similar as the Theorem 1.

In order to facilitate the proof of stability, the attributes shown in [32] are taken into consideration, when assuming that the disturbance $\Delta f_p(k)$ has the following properties.

Property 1. *$\Delta f_p(k) = O(T)$, $\Delta f_p(k) - \Delta f_p(k-1) = O\left(T^2\right)$, and $\Delta f_p(k) - 2\Delta f_p(k-1) + \Delta f_p(k-2) = O\left(T^3\right)$.*

Property 2. *Assuming $e(k+1) = \Theta e(k) + \gamma(k)$, where the magnitude of $\gamma(k)$ is of the order $O\left(T^3\right)$, and Θ is asymptotically stable ($\|\Theta\| < 1$), the magnitude of $e(k)$ is of the order $O\left(T^2\right)$ when $k \to \infty$.*

Substituting (55)–(58) into (52) yields

$$\begin{aligned} S(k) = \Lambda s(k) - \Phi\left(\Phi^T\Phi + \omega I\right)^{-1} \Phi^T \Big(\Lambda s(k) - \Gamma\hat{F}(k-1) \\ - \mathrm{K}\hat{T}(k-1)\Big) - \Gamma F(k-1) - \mathrm{K}T(k-1) \end{aligned} \tag{61}$$

where $\mathrm{K}T(k-1)$ is the switching control action, which is taking effect in the initially reaching phase [29]. Therefore, for the steady-state analysis, it is not necessary to consider the transient switching control action.

Furthermore, we assumed that there is no penalty for the $\Delta u^{mp}(k)$, namely $\omega = 0$. Then rewrite (61) as

$$S(k) = \Gamma\left(\hat{F}(k-1) - F(k-1)\right) \tag{62}$$

Next, taking (10), (49), (52) and (56) into account, we have

$$\begin{aligned} s(k+1) &= \lambda_1\left(\Delta\widetilde{f}_p(k-1) - \Delta\widetilde{f}_p(k)\right) \\ &= \lambda_1\left(\Delta f_p(k) - 2\Delta f_p(k-1) + \Delta f_p(k-2)\right) \end{aligned} \tag{63}$$

Hence, the magnitude of $s(k+1)$ is of the order $O\left(T^3\right)$ according to Property 1. $s(k+1)$ has a finite extreme value as follows

$$|s(k+1)| \le \lambda_p \tag{64}$$

where λ_p is the quasi-sliding mode bandwidth.

Therefore, it can be concluded that the nonlinear system (1) controlled by (60) satisfies the reaching condition of the QSMC in a limited number of steps.

.3. *Error bound analysis*

Define the error $e(k+1)$ as

$$(k+1) = y_m(k+1) - y_r(k+1) \tag{65}$$

Substituting (6) into Eq. (65), in view of (15) and (60), the redictive control action weight $\omega = 0$ is assumed. For the conenience of analyzing the ultimate tracking error, the transient witching control action $\hat{T}(k-1)$ is excluded [26]. Hence, the ollowing expression is obtained

$$\begin{aligned} e(k+1) &= y_m(k) + \left[\lambda_1^{-1}s(k) - \lambda_1^{-1}\lambda_2 E(k) - \Delta\hat{f}_p(k)\right. \\ &\quad + y_r(k+1) - y_m(k)] - \left(\hat{\vartheta}(k) + \delta\right) X \left(\Phi^T\Phi + \omega I\right)^{-1}\Phi^T \\ &\quad \times \left(\Lambda s(k) - \Gamma\hat{F}(k-1) - K\hat{T}(k-1)\right) + \Delta f_p(k) - y_r(k+1) \\ &= \lambda_1^{-1}s(k) - \lambda_1^{-1}\lambda_2 E(k) - \Delta\tilde{f}_p(k) - \lambda_1^{-1}s(k) + \Delta\tilde{f}_p(k-1) \end{aligned} \tag{66}$$

Rewrite (66) as

$$\begin{aligned} e(k+1) &= \left(1 - \lambda_1^{-1}\lambda_2 e^{\alpha-1}(k)\right)e(k) - \lambda_1^{-1}s(k) \\ &\quad + \Delta f_p(k) - 2\Delta f_p(k-1) + \Delta f_p(k-2) \end{aligned} \tag{67}$$

We know that $\Delta f_p(k) - 2\Delta f_p(k-1) + \Delta f_p(k-2) = O\left(T^3\right)$ nd $s(k) = O\left(T^3\right)$ by Property 1. In view of Property 2, if $\left(1 - \lambda_1^{-1}\lambda_2 e^{\alpha-1}(k)\right)\Big| < 1$, the output tracking error $e(k)$ conerges to $O\left(T^2\right)$.

. Simulation and experimental studies

To verify the effectiveness of the CFDL-DITSMC and CFDL-ITSMPC design schemes, simulation examples and an expernent are presented in this section. The experiment is implenented on the two-tank system YC-SX manufactured by 'unchuang Technology Company of China. Moreover, to show he characteristics of the proposed method, CPLD-MFAC and IN-QSMC are adopted for comparisons in simulation and expernents.

.1. *Simulation*

Consider the SISO nonlinear system as

$$\begin{aligned} (k+1) &= \frac{y(k)y(k-1)y(k-2)u(k-1)(y(k-2)-1) + u(k)}{1 + y(k-1)^2 + y(k-2)^2} \\ &\quad + d(k) \end{aligned} \tag{68}$$

vhere $d(k)$ is the external disturbance, and it is given by

$$(k) = [0.5, 0.15\sin(k/30)]\,[y(k), y(k-1)]^T \tag{69}$$

The initial states are assumed as $u(1{:}2) = 0$, $y(1{:}3) = 0$, $'(1{:}2) = 2$, and $\varepsilon = 10(-5)$. The resetting value $\hat{\vartheta}(1)$ is 0.5, nd the CFDL-DITSMC parameters are set as $\mu = 0.5$, $\eta = 0.3$, $_s = 0.0002$, $\lambda_1 = 0.3$, $\lambda_2 = 0.2$, $\alpha = 5/7$, $\omega = 0.01$, $\Delta = 0.002$, $= 3$, and $\varepsilon = 10$^(−5). The coefficient λ_1 and λ_2 are selected s $\lambda_1 > 0$ and $\lambda_2 > 0$. Especially, in the case of selecting small $_1$ or large λ_2, the control law (28) will become larger and it may ven lead to extreme chattering phenomenon. Meanwhile, in the pposite case of selecting large λ_1 or small λ_2, the control law 28) may inadequate to guarantee the tracking convergence of he closed-loop system. The CFDL-DITSMPC controller parameters ave been chosen according to CFDL-DITSMC, but with extra N = 0 and $\omega = 0.01$.

1) *Effectiveness of the proposed methods*

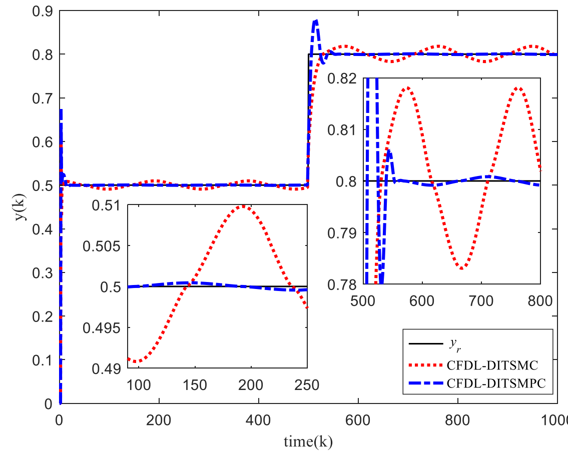

Fig. 1. Control performances of two proposed algorithms.

For the comparison purpose, simulation results of CFDL-DITSMC and CFDL-DITSMPC are given in Fig. 1. It can be observed that CFDL-DITSMPC achieves effective disturbance attenuation ability. After the 500th step, the given signal changes from 0.5 to 0.8, the system output can quickly adapt to desired signal changes and successfully converge to 0.8. Notably, the tracking error caused by the disturbance of the CFDL-DITSMPC scheme is much smaller than that of the CFDL-DITSMC scheme. Therefore, the main highlight of the CFDL-DITSMPC method compared with the CFDL-DITSMC method is that, under the drawback of the overshoot presence, the tracking error is clearly better in the steady state.

The control action and the output tracking error of CFDL-DITSMPC are demonstrated in Fig. 2(a) and (b) respectively. It is clear that there is no chattering phenomenon from Fig. 2(a). Fig. 2(c) shows that the disturbance estimation error $\Delta\tilde{f}_p(k) = \Delta f_p(k-1) - \Delta f_p(k)$ is bounded.

In CFDL-DITSMPC, the magnitude of the MPC control action is adjusting by the weight value ω. The control system outputs with the different ω are illustrated in Fig. 3. Then it can be clearly observed that there is a smaller tracking error but a larger overshoot with a smaller ω from the red dashed line in Fig. 3. Meanwhile, a larger ω will present opposite results shown in Fig. 3 with the green dashed line. When the desired signal changes, the conclusion is the same. Consequently, it is necessary to choose a suitableω to make a tradeoff between the disturbance rejection and the overshoot.

(2) *Comparison results with MFAC and NN-QSMC methods*

The CFDL-MFAC [12] scheme is

$$\Delta u(k) = \rho\left(y_r(k+1) - y(k)\right)\hat{\phi}(k) \Big/ \left(\lambda + \left|\hat{\phi}(k)\right|^2\right) \tag{70}$$

where $\lambda > 0$, $\rho \in (0, 1]$, the estimate algorithm of $\hat{\phi}(k)$ is similar to (13)–(14). The parameters of the CFDL-MFAC scheme are $\mu = 0.5$, $\eta = 0.3$, $\rho = 0.6$, $\lambda = 0.3$, and $\varepsilon = 10$^(−5).

For NN-QSMC [23], the controller structure is

$$\begin{aligned} \Delta u(k) &= \left(y_r(k+1) - y(k) - \bar{c}^T E(k) - \Delta f_P(k)\right. \\ &\quad \left. + \varepsilon \operatorname{sgn}\left(c^T E(k)\right)\right)\hat{\phi}(k) \Big/ \left(\sigma + \hat{\phi}(k)\right) \end{aligned} \tag{71}$$

where $\bar{c}^T = [1 - q - c_0, (1-q)c_0]$, $E^T(k) = [e(k), e(k-1)]$, the $\Delta f_P(k)$ of the system disturbance part is estimated by employing a RBFNN-based predictor. The controller parameters are set as $\mu = 0.5$, $\eta = 0.3$, $c_0 = 2$, $q = 0.9$, and $\sigma = 3$.

In Fig. 4, it is obvious that the output of NN-QSMC has a large overshoot in the initial state and there is a tracking error caused

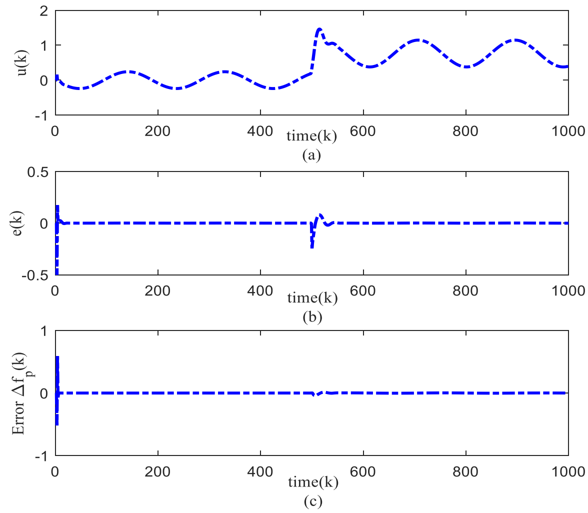

Fig. 2. Results of CFDL-DITSMPC scheme. (a) Control action. (b) CFDL-DITSMPC tracking error. (c) Disturbance estimation error $\Delta\widetilde{f}_p(k)$.

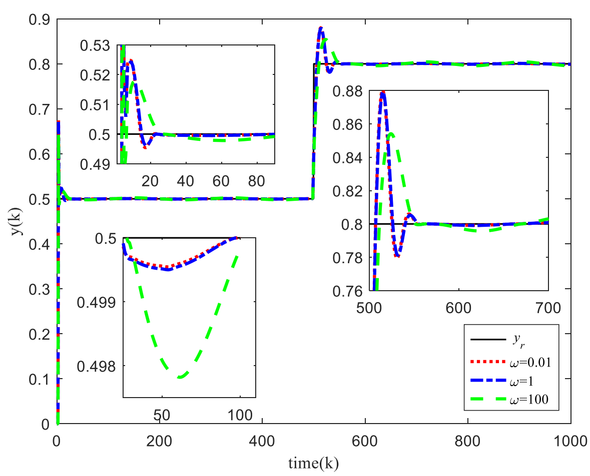

Fig. 3. The CFDL-DITSMPC outputs with a different ω.

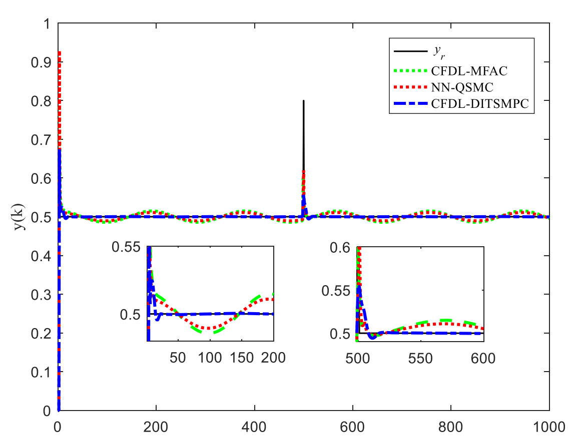

Fig. 4. Control performances comparison for three different algorithms.

by the disturbance. However, by the RBFNN-based predictor, the tracking error of NN-QSMC is smaller than that of CPDL-MFAC. Meanwhile, the output performance of CFDL-DITSMPC is superior to that of NN-QSMC. The output of CFDL-DITSMPC has

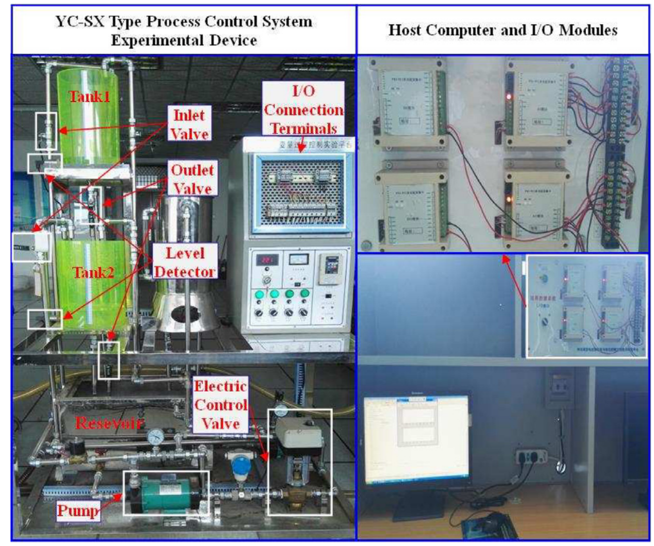

Fig. 5. The equipment of two-tank liquid level control system.

a small overshoot when adding a constant disturbance with a amplitude of 0.3 at the 500th step. When compared with CPDL MFAC and NN-QSMC, the output of CFDL-DITSMPC adapts t this change quickly, and reduces the tracking error effectively. I is notable that the perturbation estimation of CFDL-DITSMPC i more concise with disturbance estimation technique, and avoid system instability in the NN-SMC method which is caused by th random initial weights of the RBF neural network. Consequently the CFDL-DITSMPC method achieves a satisfactory performanc compared with the CPDL-MFAC and the NN-QSMC methods.

5.2. Experiments

The equipment of the two-tank process control system an the schematic are depicted in Figs. 5 and 6, respectively. Tank and Tank2 are series connection structures. A manual inlet valv and a manual outlet valve appear in each tank. A pressure senso with the accuracy of 0.25 cm is adopted to detect the tank leve Meanwhile, the type of the electric control valve is ML7420A808 produced by Honeywell Company, and it is used to regulate th flow of the pump.

I/O modules are employed to obtain the analog voltage signa 0–5 v from the pressure sensor of Tank 2, and output the analo current signal 4∼20 mA to the electric control valve, and commu nicate with the host computer via RS485. The sampling period i 1 s. The host computer software program is implemented in MAT LAB and includes analog-to-digital conversion, control algorithm the communication program, etc.

In this experiment, the control target is adjusting the contro input signal of the electric control valve, so that tank2 can main tain the desired liquid level (set as 4 cm). Valves V1, V3 and V are opened about 75%, and the valve V2 is closed.

The compared methods are the CFDL-MFAC and the NN-QSM For CFDL-MFAC, the parameters are set as $\mu = 1$, $\eta = 1$, $\rho = 0.6$ $\lambda = 0.3$, and $\varepsilon = 10$^(−5). For NN-QSMC, the main parameter are set as $\mu = 1$, $\eta = 1$, $c_0 = 3$, $q = 0.6$, and $\sigma = 3$. The RB neural network weights take random numbers. The parameter of the CFDL-DITSMPC scheme are $\mu = 1$, $\eta = 1$, $\lambda_s = 0.00$ $\lambda_1 = 0.15$, $\lambda_2 = 0.98$, $\alpha = 5/7$, $\omega = 0.01$, $N = 10$, $\delta = 3$, an $\varepsilon = 10$^(−5). The tracking performances and the control inpu currents of the electric valve of these three approaches are show in Fig. 7(a) and (b). It can be observed from the experimenta results before the 450 s that the rising times of the three method

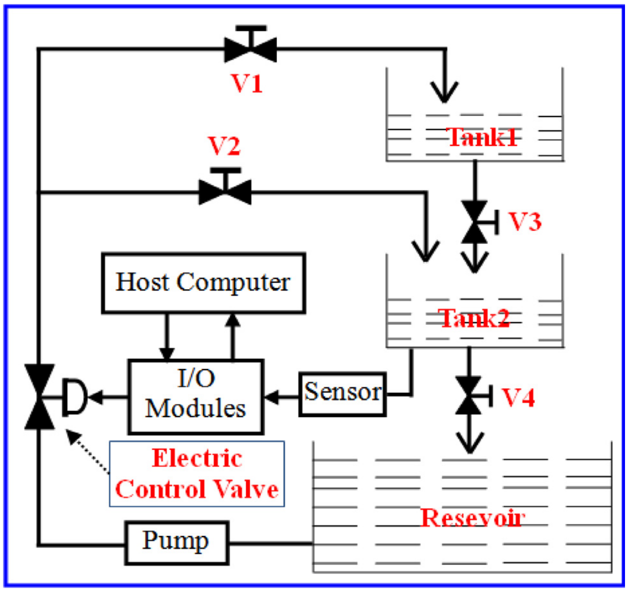

Fig. 6. The schematic of two-tank liquid level control system.

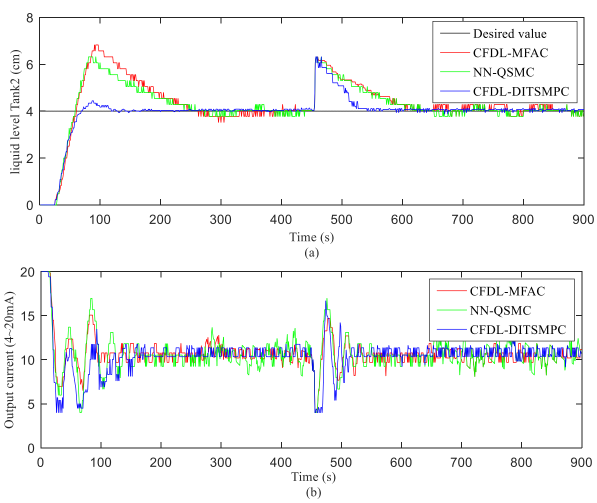

Fig. 7. The schematic of two-tank liquid level control system.

re basically the same. However, the CFDL-DITSMPC method has he smaller overshoot and the faster settling time than those of he other two methods.

In order to contrast the robustness of the three algorithms, we ›our 1000 ml water into Tank 2 at the 450 s after the system rrives at the steady state, which causes the level of Tank2 to rise y about 2 cm immediately. After the 450 s, the experimental esults are shown in Fig. 7(a), when the CFDL-MFAC and NN-)SMC make the system return to the steady state at about the 00 s, and CFDL-DITSMPC at about the 520 s. Therefore, it can e concluded that all of these three algorithms worked well for he two-tank liquid level control system. Furthermore, it can be luminated that the robust performance of the CFDL-DITSMPC nethod is superior to CFDL-MFAC and NN-QSMC.

. Conclusion

In this paper, based on the CFDL technique and the DITSMC nethod, a novel model-free adaptive control scheme, including he CFDL-DITSMC and the CFDL-DITSMPC, is presented for a class of discrete-time nonlinear systems with disturbances. With the advantage of the CFDL technique, CFDL-DITSMC with the disturbance estimate technique is proposed, when the controller design does not require model information. Moreover, the CFDL-DITSMPC method combines the MPC technique and CFDL-DITSMC to enhance the tracking accuracy. Furthermore, the effectiveness of CFDL-DITSMPC is verified by numerical simulations and the liquid level control system. Considering that the CFDL-DITSMPC control strategy possesses more control parameters, future research could focus on the control parameter adaptive method for the CFDL-DITSMPC.

Acknowledgment

Conflict of interest

There is no conflict of Interest.

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