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Experimental Comparison among Three Typical Data-Driven Control Algorithms

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Abstract: The differences, similarities and insights of three typical data-driven control algorithms, model free adaptive control (MFAC), iterative feedback tuning (IFT) and virtual reference feedback tuning (VRFT), are briefly discussed, and these differences, similarities and insights are certified through a series of experiments on the three-tank water system in our university lab.

Keywords: data-driven control, model-free adaptive control, iterative feedback tuning, virtual reference feedback tuning.

I. INTRODUCTION

Data-driven control methods focus on finding controller, merely using input/output data of the control system. Up to now, there exist a few data-driven control methods [1], such as iterative learning control (ILC), unfalsified control (UC), virtual reference feedback tuning (VRFT), iterative feedback tuning (IFT), model free adaptive control (MFAC), etc. In order to enhance their applications and make a clearly understanding the drawbacks and advantages of these data-driven control methods in practice, three typical data-driven control algorithms (MFAC, IFT and VRFT) are briefly discussed and the differences, similarities and insights of these methods are certified through a series of experiments.

The rest of this paper is organized as follows. In section 2, three typical data-driven control methods are brief discussed. In section 3, a series of experiments are given to demonstrate the correctness of the discussion in section 2. The conclusions are drawn in section 4.

II. Three Typical Data Driven Control Methods

1. Model-Free Adaptive Control

Model-free adaptive control method was proposed for a class of general SISO nonlinear discrete time systems by Hou [2]. Instead of identifying a, more or less, known global nonlinear model of the plant, an equivalent dynamical linearization time varying model are built along the dynamic operation points of the controlled plant using a novel concept called pseudo-partial derivative (PPD), which is estimated merely using the I/O data of the controlled plant. The dynamic linearization method includes the compacted form dynamic linearization (CFDL), the partial form dynamic linearization (PFDL), and the full form dynamical linearization (FFDL).

In detail, the MFAC approach can be described by the following steps: (a) Choose one dynamic linearization method, such as, CFDL. (b) Design the MFAC algorithm based on the selection in step 1, which includes a PPD updating law, a control input learning law, and a reset algorithm. (c) If the system output error is 0, then the control input remains value of the previous time instant, otherwise go to Step d. (d) Estimate the time varying parameter PPD merely using the on-line I/O data. (e) Update the control input using the PPD estimate values iteratively. (f) Repeat from step c.

Compared with other adaptive control schemes, the MFAC method is a data-driven control approach, and has several attractive properties, which make it suitable for many practical control tasks. First, the MFAC algorithm just depends on the real time measurement data of the controlled system. Secondly, the MFAC algorithm does not require any external testing signals and any training process they are necessary for the neural networks based nonlinear adaptive control and can be called a less expensive and lower cost controller. Thirdly, the MFAC algorithm is simple and easily implemented with minimum computational burden, and has strong robustness. Fourthly, under some assumptions, the convergence and stability of the presented MFAC methods can be guaranteed with rigorous mathematic analysis [1, 3-4]. Fifthly, the results of the MFAC for SISO nonlinear discrete-time systems have its corresponding extended ones for the MISO, and MIMO nonlinear systems. Finally, MFAC has been successfully implemented in many practical fields, such as, the chemical industry [5-6], the linear motor control, the injection modelling process [7], the PH value control [8], and so on.

2. Virtual Reference Feedback Tuning

The VRFT method was proposed by Guardabassi and Savaresi [9], which is a "one-shot" direct data-based controller design method. The procedure of VRFT can be summarized as follows: (a) Collect a batch of input/output data coming from the plant, (b) Calculate the virtual error signal, the virtual input of controller, (c) Calculate the virtual output of controller, (d) Use the batch of virtual input/output data of controller, to identify the optimal controller parameters using. Till now, a few applications of VRFT could be found in reference [10-12].

3. Iterative Feedback Tuning

The IFT method was proposed by Hjalmarsson [13], which considers the controller design as a parameter optimization problem. The procedure of VRFT can be summarized as follows: (a) Perform a normal experiment on the closed loop controlled system with the reference signal and collect N measurements of the output signal $y^{(1)}(\boldsymbol{\theta}_i)$ of the plant, (b) Perform a gradient experiment on the closed loop controlled system with the reference signal $r - y^{(1)}(\boldsymbol{\theta}_i)$ and collect N measurements of the output of the plant which can be expressed as $y^{(2)}(\boldsymbol{\theta}_i)$, (c) Take $\frac{\partial \hat{y}}{\partial \boldsymbol{\theta}}(\boldsymbol{\theta}_i) = \frac{1}{\mathrm{C}(\boldsymbol{\theta}_i)} \frac{\partial \mathrm{C}}{\partial \boldsymbol{\theta}}(\boldsymbol{\theta}_i) y^{(2)}(\boldsymbol{\theta}_i)$ as gradient approximation, (d) Estimate the controller parameters using the gradient approximation. Till now, a few applications of IFT could be found in reference [14-15].

Table 1 The characteristics of three data-driven control methods

Method	MFAC	VRFT	IFT
Controlled Plant	General nonlinear plant	Linear time invariant plant	Linear time invariant plant
feature	● Adaptive control of the plant whose parameters and structure may be time-varying ● Low computational costs ● Online	● Parameters tuning method for the controller whose structure is given ● "One-shot" method using a batch of input/output data of the plant ● Offline	● Parameters tuning method for the controller whose structure is given ● Iterative method, for each iterative using two batches of input/output data of the plant ● Offline
Factors affecting performance	● Control input length constant of linearization	● The structure of the controller ● The quantity of the batch of data	● The structure of the controller ● The quantity of the batch of data ● The initial value of parameters of the controller
Assumptions	● Generalized Lipschitz	● Structure of the controller needs to be given ● Reference model is invertible, and cannot be 1	● Structure of the controller needs to be given ● All signals of the loop remain bounded throughout the iterations
Others	● A series of dynamical linearization methods ● A series of methods for design controller ● Extended to MIMO plant ● Having BIBO stability proof ● Modularized design	● Extended to nonlinear plant ● Extended to MIMO plant	● Extended to nonlinear plant ● Extended to MIMO plant

4. Characteristics of Three Methods

The characteristics of three typical data-driven control methods are summarized as table 1.

III. EXPERIMENT

The control performance of MFAC [5], IFT [12] and VRFT [18] has been evaluated on an equipment of Three Tank Water System, which is manufactured and provided by Tianhuang Technology Company in China.

The sampling time is adopted 1s and the simulation time is 400s. The set point of T3 is 5cm. The initial condition of system is $u(0)=0,\ \ y_1(0)=0,\ \ y_2(0)=0,$ $y_3(0)=0$, where u denotes the flow rate of upper tank, and y_1, y_2, y_3 denote the liquid-level of upper, middle and lower tank, respectively. The parameters of three data-driven control methods, experimental conditions and parameter tuning results are shown in table 2.

The performance of MFAC method is shown in Fig.1. From Fig.1 we can see that the MFAC with L = 5 gave better control performance. However, larger L will lead to more parameters which should be adjusted online, resulting in increasing the online computation. In addition, MFAC is an adaptive control method, thus there are few restrictions on the sampled data.

The performance of VRFT method is shown in Fig.2. From Fig.2 we can see that larger quantity of data will lead to better control performance for the same controller order, while higher order of controller will lead to better control performance for the same quantity of data. However, offline computation will increase with the growth of controller order and quantity of data. Moreover, the experiment time depends on the quantity of data.

Table.2 experimental conditions and parameter tuning results

Scenario	Control algorithm	Controller order	Quantity of data	Iterative time	Initial parameters of controller	Final parameter of controller
1	MFAC	L=3	On-line	0	$\hat{\Phi}(0)=\begin{bmatrix}0.5 & 0 & 0\end{bmatrix}^T$ $\rho=1,\lambda=1,\eta=1,\mu=1$	$\hat{\Phi}(k)$ is estimated by on-line I/O data $\rho=1,\lambda=1,\eta=1,\mu=1$
2	MFAC	L=5	On-line	0	$\hat{\Phi}(0)=\begin{bmatrix}0.5 & 0 & 0 & 0 & 0\end{bmatrix}^T$ $\rho=1,\lambda=1,\eta=1,\mu=1$	$\hat{\Phi}(k)$ is estimated by on-line I/O data $\rho=1,\lambda=1,\eta=1,\mu=1$
3	IFT	I=3	400	5	$K_1=7.5, K_2=-8, K_3=1$	$K_1=9.561, K_2=-11.682, K_3=2.648$
4	IFT	I=3	200	5	$K_1=7.5, K_2=-8, K_3=1$	$K_1=13.431, K_2=$ -18.973, $K_3=6.066$
5	IFT	I=5	400	5	$K_1=7.5, K_2=-8, K_3=1$ $K_4=0, K_5=0$	$K_1=8.62, K_2=-8.92, K_3=0.555, K_4=-0.585, K_5=0.85$
6	IFT	I=5	200	5	$K_1=7.5, K_2=-8, K_3=1$ $K_4=0, K_5=0$	$K_1=11.56, K_2=-12.699, K_3=0.453, K_4=-0.133, K_5=1.342$
7	VRFT	I=3	400	"one shot"	$K_1=7.5, K_2=-8, K_3=1$	$K_1=10.99, K_2=-11.45, K_3=0.6728$
8	VRFT	I=3	200	"one shot"	$K_1=7.5, K_2=-8, K_3=1$	$K_1=12.19, K_2=-12.49, K_3=0.61$
9	VRFT	I=5	400	"one shot"	$K_1=7.5, K_2=-8, K_3=1$ $K_4=0, K_5=0$	$K_1=12.04, K_2=-11.78, K_3=-2.045, K_4=0.747, K_5=1.365$
10	VRFT	I=5	200	"one shot"	$K_1=7.5, K_2=-8, K_3=1$ $K_4=0, K_5=0$	$K_1=14.04, K_2=-13.08, K_3=-3.801, K_4=0.84, K_5=2.526$

The performance of IFT method is shown in Fig.3. From Fig.3 we can see that after iterative optimization of controller parameters, the performance of controlled system is not improved significantly in four scenarios. The reason may lie in that the step size γ is not selected suitably, and after 5 iterations controller parameters have not converged to the optimal values. It is worth to point out that the experiment for IFT method is very time-consuming, so only five iterations are taken in this paper.

To compare the performance of three methods, choosing the best parameters for each algorithm, make liquid-level of lower tank achieve the reference level, when k=250s, close the inlet valve of upper tank and open the inlet valve of lower tank. Because of omitting two tanks, the order and delay time of plant will become smaller. The performances of three algorithms are shown in Fig.4. From Fig.4 we can see that during the first 250s, the performance MFAC and VRFT is satisfactory, but the performance of IFT is not satisfactory because the controller parameters have not converged to the optimal values. After time 250s, the system structure and parameters changed, and the performance of MFAC is best because the PPD vector parameter $\hat{\Phi}(k)$ of MFAC is updated by on-line I/O data of plant.

VI. CONCLUSION

Through above theoretical analysis and experimental comparison, we obtain the conclusion of this paper as follows: (a) The MFAC method uses the on-line I/O data of controlled plant only. The MFAC mechanism does not require any external testing signals and any training process. The MFAC scheme is simple and can be easily implemented, and has minimum computational burden and strong robustness. (b) The optimal parameters of the VRFT controller are obtained by an optimization procedure using a batch of off-line I/O data. The control performance depends on the controller structure, reference model, and quantity of collected I/O data. However, in practice, it is hard to select the appropriate reference model and controller structure. The VRFT scheme has compromised computational burden. (c) The IFT method is based on an iterative tuning of the controller parameter vector along the gradient direction of some control criterion. In each iteration, the controller parameters of IFT method are updated by using off-line I/O data from two experiments. The performance of IFT depends on the initial controller, and quantity of collected I/O data, step-size. The basic requirement of parameters convergence is that all signals of the loop remain bounded throughout the iterations, it is implies that the controller in each iteration must be stable. (d) In the last experiment, the performance of MFAC is best because the PPD vector parameter $\hat{\Phi}(k)$ of MFAC is updated by on-line I/O data of plant. While the performance VRFT and IFT is not satisfactory because they are off-line controller parameters tuning method, and can not deal with the time-varying plant.

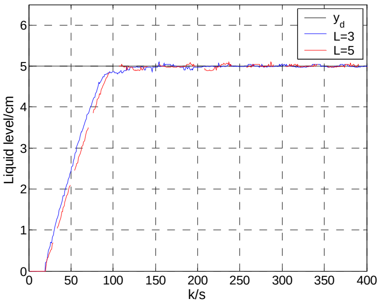

Fig. 1 The control performance of MFAC

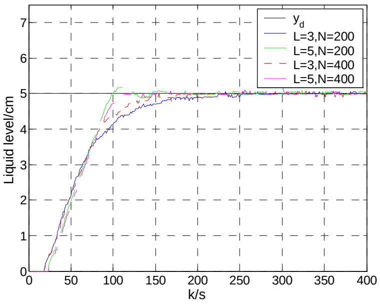

Fig. 2 The control performance of VRFT

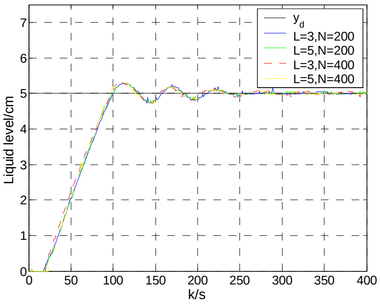

Fig. 3 The control performance of IFT

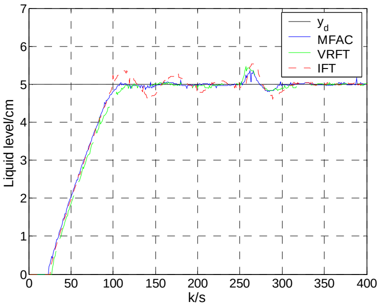

Fig. 4 The comparison among three methods

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