A Novel Interactive System Identification and Control Toolbox Dedicated to Real-Time Identification and Model Reference Adaptive Control Experiments

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Abstract

This paper proposes a control-oriented identification toolbox with a set of real-time interactive computer-aided experiments to analysis parametric system identification techniques and adaptive control concepts. The proposed experiments are highlighted through a user-friendly graphical user interface (GUI) which is developed in Matlab/Simulink® environment. The identification and control methods considered here include; process reaction curve method, off-line and on-line parameter identification and model reference adaptive control technique (MRAC); this aspect of the paper makes it a beneficial guide to a large number of readers.

1. Introduction

Advances in software and hardware have made it possible to develop more capable computer based learning resources e.g. simulation tools enabling us to carry out the experimental studies in an interactive environment. Furthermore, several approaches have been proposed to enhance the control engineering programme include tele-lab or virtual lab concepts [1-3]. However, in the present study, a set of in-laboratory identification and adaptive control concepts are presented through an interactive toolbox. Such a computer-aided experimental infrastructure gives the students' considerable degrees of freedom to prototype alternative methods on a selected test setup easily [4]. The experimental setups have been selected carefully to stipulate diversity in various applications of system identification and model reference adaptive control methods.

In control divisions, although the linear control concepts have well-established learning resources and instructional materials, the teaching tools for system identification and adaptive control concepts need to be improved [4]. Most of the students, who take a course in system identification and adaptive control, are having trouble to relate the theory and practice due to the examples provided in the text are too abstract. In order to cope with the aforementioned problem, we proposed an interactive toolbox for system identification and control experiments in real-time laboratory environment.

Recent trends in educational research assert that the traditional learning strategies are not sufficient to teach real-world engineering problems and applications [4]. Undoubtedly, it needs to be improved the instructional methods, changed the role of instructor, reorganized learning outcomes and assessment methods for strengthening student engagement and providing high participation [4]. Furthermore, when the laboratory experiments are considered as instruments for efficient teaching, experiment design becomes further interesting. However there is not a well-defined way to do this. Therefore the design of courses having such goals becomes an art. With this motivation in mind, an interactive student-centered laboratory experiments are proposed [4].

System identification is defined as an art of building the mathematical models of dynamical systems from observed input-output data [4-8]. So that, identification studies have acted a key role to combine real world and mathematical model of the system. This motivates the researchers to explore the new identification methods for acquiring perfect model and efficient model-based control algorithms. There have been various methods available to develop a dynamic model of a real system, the methods are described under several headlines namely; linear, nonlinear, white-box, grey-box and black-box. White-box method is used to formalize the model based upon the physic laws such as principles of Newton's laws. A Grey-box method, mixture of black-box and white-box, is partially known from physics laws and the rest is reconstructed from experimental data. On the other hand in the black-box methods, it is assumed that all model parameters are unknown but adjustable and predictable without considering the physical system. Among these methods, black-box is the most applied one to the real life problems [5-8], therefore we highlighted the black-box methods with off-line and on-line parameter estimation both in open loop and closed loop conditions. The off-line approach use specific test inputs then try to establish a model, however, the on-line approach estimate the model parameters by using recursive methods such as; recursive least squares, recursive instrumental variables, least mean squares or neural networks etc [5-8]. Naturally all that methods have an iterative manner that makes them led to adaptive control and controller tuning algorithms in control system society.

Several system identification tools have been proposed e.g. J.L Guzman et al. presents an interactive software tool in [9]. J.F. Haffner et al address frequency-domain techniques with computer aided applications [10]. Klerk et al focuses on closed loop system identification with an experimental study [11]. J.D. Alvarez et al. focuses on the perspective of control-relevant identification through the use of interactive tools [12]. M. Furat et al. highlights some of step response analysis methods for smooth introduction of identification world to undergraduate students [13]. Another useful real-time software tool is elaborated by D.J. Lim for the identification and control of dynamical systems [14]. Furthermore, Özbek et al. proposes a novel instructional strategy and assessment methods for system identification and adaptive control courses [4].

The rest of the paper is organized as following. The next section describes the laboratory equipment. The third section involves the process reaction curve method with different algorithms namely first order method (FOM), first order plus dead time (FOPDT) and the modelling results of aforementioned methods are demonstrated on DC motor unit, furthermore online parameter estimation techniques are highlighted in open-loop conditions with the results of PT326 process trainer, this experiment is devoted to parameter estimation with recursive methods, lastly MRAC is highlighted with experimental results on permanent magnet DC motor unit. Finally, concluding remarks are given at the end of the paper.

2. Laboratory Equipment

The laboratory systems, which have been widely used both to test the novel identification algorithms and to teach well-known model-based control techniques, are described in this section. The first elaborated system is a heating process (PT326) which consists of an air tube, heating element, temperature sensor and an air damper as illustrated in left hand side of Fig. 2. The temperature can be measured at three different locations along the tube. The main advantage of using such a process is to enable the study of several effects such as: pure time delays, transfer lags, PI or PID control and nonlinear effects in the control action. The second system is an electromechanical unit consists of DC motor and tachogenerator connected via a shaft; the system is mounted on the DIGIAC1750 educational process instrumentation training set. DC motors are frequently used both in industry and academia; therefore to analysis of a DC motor behavior is a fundamental step to constitute a beneficial effort for many practical applications.

The equipment's employed in this laboratory are; a personal computer having Intel®core TM(2) Quad CPU Q850 @2.7GHz processor, 4GB RAM, 1024 MB VGA card and also a data acquisition card having 32 analogue input- 16 analogue output, 48 Digital I/O, 250Ks/s-16 bit maximum sampling rate and resolution [4]. In order to achieve real time implementation of algorithms, the systems are linked to a computer via NI-PCI-6229 data acquisition board from National Instrument Company which is a multifunction data acquisition card. The developed platform is designed with MATLAB/ Real-Time-Toolbox [4].

2.1. Interactive GUI

The experiments are constituted with an interactive GUI in order to highlight all steps of system identification and adaptive control. The learning tool involving several panels such as: the input design, data acquisition, identification and analysis. The system identification GUI includes all the experimental steps (input design, model structure, parameter estimation and validation, effects of each variable) in the same screen [4], [13]. The key point of each experimental infrastructure is enabling the user to substitute their own programs to the related GUI which is considered by dividing the interface into two main panels. The system figure, the input design module, the Simulink models are shown on the left panel while the selected methods, model parameters, model and real output, and the modelling error can be displayed on the right panel [4],[13], see Fig.2. This situation allows the students to focus on analyzing, prototyping the identification methods with reduced development time without any involvement in the programming process, at the same time such experimental infrastructure improves interactivity during the experimentations.

3. Experimental studies

This part is devoted to analyzed experimental studies which composed of, prototyping periods, generating a perturbation signal, choosing a model with different order and importing the necessary work space data that should be identified. The experiments are constituted with an interactive experimental infrastructure which is enabling the students to substitute their own programs to the related GUI which consists of several panels such as: the input design module, data acquisition, estimation panels and analysis. 9

3.1 Process reaction curve modelling

The central notion of the method is applying a step input which is frequently used for analyzing of dynamical systems and tested a conventional controller in feedback systems. In order to obtain an accurate process reaction curve, the system is allowed to reach steady state [13].

The elaborated methods are; first order method (FOM), First order plus dead time method (FOPDT). As a first approach, the FOM transfer function is highlighted in (1) where K is the steady-state gain and τ is the time constant [13].

$$G(s)=\frac{K}{\tau s+1}=\frac{Y(s)}{U(s)}\in R(s), \tag{1}$$

Yet another sufficient characterization method is well known one is called first order plus dead time method, the transfer function can be presented as.

$$G(s)=\frac{Ke^{-t_d s}}{\tau_p s+1}\approx\frac{K}{(\tau_p s+1).(t_d s+1)} \tag{2}$$

In the proposed method two key point is introduced by td and τ_p are calculated by

$$\begin{aligned} t_d &= 1.3t_{35.3}-0.29t_{85.3} \\ \tau_p &= 0.67(t_{85.3}-t_{35.3}) \end{aligned} \tag{3}$$

The step signals with different amplitudes are applied to the system enabling to analyze different shaft speed, and then process reaction curve is obtained graphically to estimate the model parameters. During this it was avoided exceeding the linear region of each set-up.

The obtained model of DC motor with process reaction curve methods can be on the identification GUI, see Fig.1. [13].

3.2 Online Identification Method

The key point of the real-time identification is to determine the perturbation signal. The different choice of perturbation signals can be designed from input design module such as; step, square wave signals, pseudorandom binary sequence (PRBS), Gaussian distributed noise [4-8].

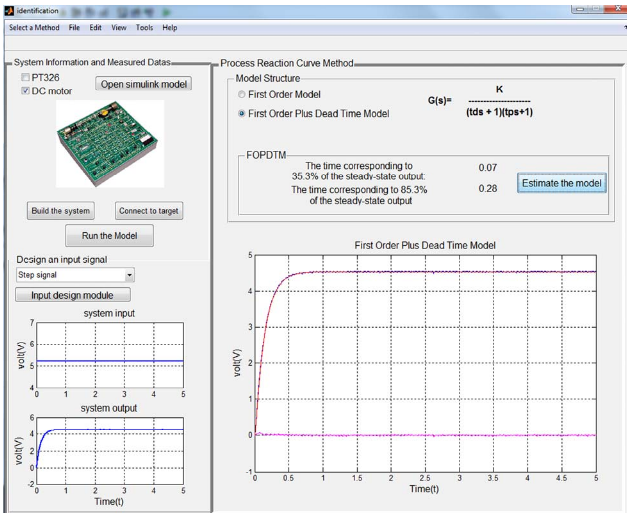

Fig. 1. An example of toolbox screen for process reaction curve identification

The reference signal should be sufficient to excite the slowest and highest system modes, thus the period and length of sequence should be chosen properly. The determination of the frequency of depends on the frequencies to be identified and the length of sequence should be at least settling time of the system. On the other hand, to summarize the test or dither signal should have an amplitude level and distribution which does not violate the linear operating range of the system or drive the system into undesirable operating regions. When setting up a test signal for recursive estimation it is most important that the signal *u(t)* is constant between sample intervals. In practice this means transitions in the test or dither signal should be synchronized with sampling device. This will occur naturally if the test/dither signal is generated in the computer used for recursive estimation.

Although recursive least squares have similar properties with their counterparts in offline least squares setting, the method is a popular technique displaying several prominent features such as straightforward algorithm and fast parameter convergence [5-8]. In the following, we describe the design philosophy. By assuming that the error $e(k)$ is uncorrelated noise with variance σ_e^2 and $E\{e(t)\} := 0$. The plant parameters, a_i and b_j are unknown and should be estimated. The estimated model is given [6-8]:

$$G_e(z^{-1}) = z^{-d}\frac{B_e(z^{-1})}{A_e(z^{-1})} \in R(z^{-1}) \tag{4}$$

where;

$$\left\{\begin{array}{l} A_e(z^{-1}) = 1 + \hat{a}_1 z^{-1} + \hat{a}_2 z^{-2} + \ldots + \hat{a}_n z^{-n_n} \in R(z^{-1}) \\ B(z^{-1}) = \hat{b}_0 + \hat{b}_1 z^{-1} + \hat{b}_2 z^{-2} + \ldots + \hat{b}_n z^{-n_m} \in R(z^{-1}) \end{array}\right\} \tag{5}$$

The orders of the estimated plants are n_m and n_n moreover $A_e(z^{-1})$ and $B_e(z^{-1})$ represents model polynomials, respectively, with $n_m \le n_n$ and the parameter vector is given [6-8]:

$$\hat{\theta} = [\hat{a}_1, \hat{a}_2, \ldots, \hat{a}_{n_a} \hat{b}_0, \ldots \hat{b}_{n_b}]^T \tag{6}$$

The estimated model output is presented:

$$\hat{y}(k) = \phi^T(k)\hat{\theta}(k-1) \tag{7}$$

The parameter vector is written as:

$$\hat{\theta} = \left[\phi^T(k)\phi(k)\right]^{-1}\left[\phi^T(k)y(k)\right] \tag{8}$$

It is needed to be whenever the information is coming about input/output samples that are in each sampling interval in RLS method. A supposed mode from the previous sampling period $\hat{\theta}(k-1)$ is used for assessment of $\hat{y}(k)$ system output in the given sampling period. Estimated system output is compared with the real system output $y(k)$ and on the basis of the obtained difference, an error signal $\varepsilon(k)$ is generated. $P(k)$ presents so called covariant matrix, is presented [6-8]:

$$P(k) = \left[\phi^T(k)\phi(k)\right]^{-1} \tag{9}$$

The model prediction error $\varepsilon(k)$ is the difference between the plant output and the estimated model which is a key variable is RLS, defined as:

$$\varepsilon(k) = y(k) - \phi^T(k)\hat{\theta}(k-1) \tag{10}$$

The error is used to update by using the matrix inversion lemma [6-8]. The parameters are estimated as:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x(k)\varepsilon(k) \tag{11}$$

Where the estimator covariance matrix $P(k)$ is updated using [8].

$$P(k) = \frac{1}{\lambda}P(k-1)[I_z - \frac{\phi(k)\phi^T(k)P(k-1)}{\lambda + \phi^T(k)P(k-1)\phi(k)}] \tag{12}$$

The error and the vector of unknown parameters are obtained:

$$\left\{\begin{array}{l} \varepsilon(k) = y(k) - x^T(k)\hat{\theta}(k-1) \\ \hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x(k)\varepsilon(k) \end{array}\right\} \tag{13}$$

The students evaluate the parameters effects on the model by observing root mean square error and related validation tests are performed for each selected model. The students are requested to repeat the experiments with different parameter configurations to figure out the role of each parameter in the overall result. The GUI screen is highlighted in Fig.2. [15].

The effects of forgetting factors are also discussed; faster parameter convergence is obtained if the forgetting factor is reduced, but this leads to noise amplification [6-8].

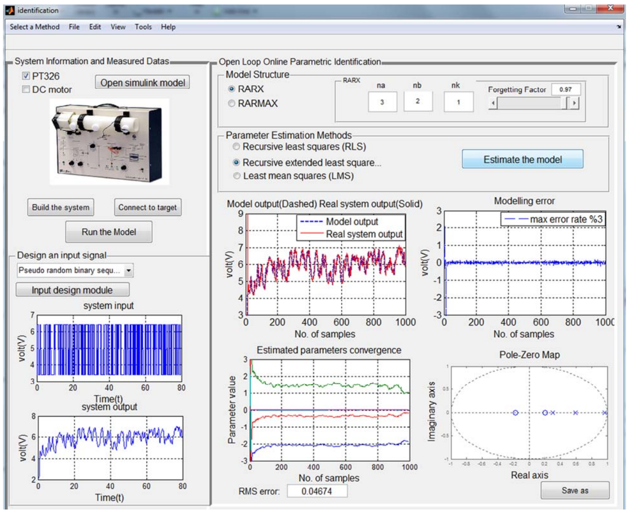

Fig. 2. An example of toolbox screen for online identification

Table 1. Continuous and Discrete Model of PT326

Continuous Model and Transfer Function	Discrete Model and Transfer Function
$\dfrac{Y(s)}{U(s)}=\dfrac{Ke^{-\tau_d s}}{\tau s+1}$	$G_1(z^{-1})=\dfrac{0.009264\,z^{-1}}{1-1.807\,z^{-1}+0.8145\,z^{-2}}z^{-1}$
$\dfrac{Y(s)}{U(s)}=0.61\dfrac{e^{-0.54s}}{1+1.57s},$	$G_2(z^{-1})=\dfrac{0.007855\,z^{-2}}{1-2.091\,z^{-1}+1.439\,z^{-2}-0.341\,z^{-3}}z^{-2}$

3.3 Model Reference Adaptive Control

This experiment includes the application and performance comparison of the MRAC with MIT rule and Lyapunov approach. The experiment is composed of constituting mechanical unit and digital unit of DC motor, design of a model reference adaptive controller and implementation of it. The final stage contains efforts of searching for the best set of parameters. In the case of system parameters are not known, the desired model is followed by defining an adaptive law which updates the control signal parameters online. In MRAC strategy the performance specifications are given in terms of a model, is based on to minimize the error between the responses of real system and a desired reference model which follows the reference signal. The students analyze the effects of controller parameters, adaptation gains and adaptation algorithms, during the experiment [4], [16-17]. Adaptation algorithms are obtained for both first and second order reference models. As an example of the applied method, first order plant and first order reference model can be defined as [16-17]:

$$\left\{\dot{y}_m+a_m y_m=b_m r,\qquad Y_m(s)=G_m(s)R(s)=\frac{b_m}{a_m+s}R(s)\right\} \tag{14}$$

$$\left\{\dot{y}_p+ay_p=bu,\quad Y_p(s)=G_p(s)U(s)=\frac{b_p}{a_p+s}U(s)\right\} \tag{15}$$

The plant output is shown with Y_p and model output is defined with Y_m. By taking the differences of these output signals we obtain the tracking error e and choosing the control law as [16-17]:

$$u=\hat{a}_r(t)r+\hat{a}_y(t)y \tag{16}$$

where a_r and a_y are variable feedback gains. The closed loop dynamics are obtained as following:

$$y=-(a_p-\hat{a}_y b_p)y+\hat{a}_r b_p r(t) \tag{17}$$

The goal of MRAC is providing as possible as good matching between the plant output and reference model. Indeed, if the plant parameters are known, the following values of control parameters.

$$a_r^*=\frac{b_m}{b_p},\quad a_y^*=\frac{a_p-a_m}{b_p} \tag{18}$$

which leads to closed loop dynamics as:

$$\dot{y}=-a_m y+b_m r \tag{19}$$

This is identical to the reference model dynamics and yields zero tracking error. The control law allows the possibility of perfect model matching. In the adaptive control approach plant parameters are unknown and adaptation law search the appropriate gains based on the tracking error in order to make y_p and y_m asymptotically. The important point about the application of model reference adaptive control is choosing adaptation algorithm which varies the control parameters online. In order to implement MIT rule a gradient based adaptation algorithm is designed as following: $e=y-y_m$ be the tracking error [17]. The parameter errors are defined as the difference between the controller parameters provided by the adaptation law and the ideal parameters [16-17].

$$\tilde{a}(t)=\begin{bmatrix}\tilde{a}_r\\ \tilde{a}_y\end{bmatrix}=\begin{bmatrix}a_r-a_r^*\\ a_y-a_y^*\end{bmatrix} \tag{20}$$

The dynamics of tracking error can be found by subtracting.

$$\dot{e}=-a_m(y-y_m)+(a_m-a_p+b_p\hat{a}_y)y+(b_p\hat{a}_r-b_m)r \tag{21}$$

$$e=\frac{b_p}{s+a_m}(\tilde{a}_r r+\tilde{a}_y y)=\frac{1}{a_r^*}M(\tilde{a}_r r+\tilde{a}_y y) \tag{22}$$

A step signal is used as the reference input and the reference model is determined as to give an underdamped response to reference signal [16]. Results show that the system settled at the desired position in a finite time and the control parameters are updated successfully. Thus the students gain an insight about defining an adaptive control law when the parameters of the plant are not known [16].

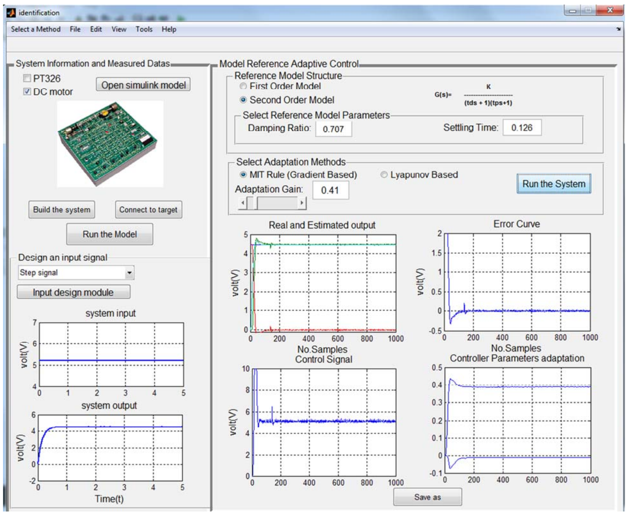

Fig. 3. An example of toolbox screen for Model reference adaptive control experiment

4. Conclusions

Control engineering is of great importance since; the control technology is the cornerstone of the new engineering revolution of many technological subjects such as automotive, aerospace systems, chemical processes, transportation systems, medical systems. This paper described a set of experiments to those mastering on system identification and model reference adaptive control. Despite undergraduate laboratories in control engineering have some degree of maturity; courses like system identification still necessitate particular attention. One of the main complaints of the students is too theoretical material in nature of the system identification courses and related topics, and the examples provided in the text are too abstract. To handle this common complaint, a set of system identification and control toolbox is proposed for real-time laboratory control experiments. Standard experimental setups have been used and repeatability of the experiments has been ensured.

Model development of some benchmark processes is explained step by step with an educational graphical user interface (GUI). Furthermore, the methods chosen for prototyping identification strategies are also widely used in system identification theory, this aspect of the paper makes it a beneficial guide to a large number of readers.

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