ITERATIVE FEEDBACK TUNING APPROACH TO A CLASS OF STATE FEEDBACK-CONTROLLED SERVO SYSTEMS

Mircea-Bogdan Rădac, Radu-Emil Precup
Dept. of Automation and Appl. Inf., "Politehnica" University of Timisoara
Bd. V. Parvan 2, 300223 Timisoara, Romania

Emil M. Petriu
School of Information Technology and Eng., University of Ottawa
800 King Edward, Ottawa, ON, K1N 6N5 Canada

Stefan Preitl, Claudia-Adina Dragoş
Dept. of Automation and Appl. Inf., "Politehnica" University of Timisoara
Bd. V. Parvan 2, 300223 Timisoara, Romania

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Abstract: An original control structure dedicated to a class of second-order state feedback control systems is presented in the paper. The controlled processes are accepted to be characterized by second-order servo systems with integral component. Optimal state feedback control systems are designed for those processes making use of the Iterative Feedback Tuning (IFT) approach. The state feedback control system structure is extended with an integral component to ensure the rejection of constant disturbances. A case study concerning the position control of a DC servo system with backlash is included. Real-time experimental results validate the theoretical part of the IFT approach.

1 INTRODUCTION

The second-order servo systems with integral component are applied widely as controlled processes in real-world applications including mechatronics, electrical drives, sub-systems in power plant control systems, positioning systems in manipulators, mobile robots, machine tools, flight guidance and control (Škrjanc et al., 2005; Gomes et al., 2007; Petres et al., 2007; Barut et al., 2008; Costas-Perez et al., 2008; Denève et al., 2008; De Santis et al., 2008; Orlowska-Kowalska and Szabat, 2008; Precup et al., 2008b; Vaščák, 2008). Those controlled processes are acknowledged as particular cases of benchmark systems (Åström and Hägglund, 2000; Isermann, 2003; Horváth and Rudas, 2004; Kovács, 2006). Accepting that they are linearized versions of nonlinear servo systems, the parameters are variable with respect to the operating points. Hence the parameter variation makes their control a challenging task when very good control system performance indices are required. Their control problems become even more challenging when low-cost automation solutions are needed in the design and implementation of the control system structures.

One control solution to cope with the accepted class of processes described is represented by state feedback control systems. Since the main control aims, high performance indices in reference input tracking and regulation with respect to several types of load disturbance inputs, are difficult to be fulfilled, one typical approach is to design optimal control systems. The improvement of the control system performance indices (fore example settling time and overshoot) is enabled by the minimization of appropriately defined objective functions resulting in optimal state feedback control systems. An alternative to the minimization of the objective functions is represented by Iterative Feedback Tuning (IFT) (Hjalmarsson et al., 1994, 1998). IFT

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algorithms make use of the input-output data measured from the closed-loop system during its operation to calculate the estimates of the gradients and Hessians of the objective functions. Several experiments are done per iteration and the updated controller parameters are calculated based on the input-output data and the estimates.

The application of IFT to one-degree-of-freedom controllers needs two experiments per iteration. The first experiment is referred to as the normal one and it corresponds to the usual operation of the control system. The second experiment is the gradient one. The reference input in the gradient experiment is the control error of the first experiment. An additional normal experiment is needed in case of two-degree-of-freedom controllers. Even more experiments are needed to tune the state feedback controllers and the Multi Input-Multi Output (MIMO) ones. So it is natural to strive for the alleviation of the number of experiments (Hjalmarsson and Birkeland, 1998; Hjalmarsson, 1999; Jansson and Hjalmarsson, 2004).

The paper aims three main contributions. The first contribution of the paper is the proposal of an IFT algorithm resulting in a method to obtain the partial derivatives needed in the calculation of the gradient of the objective function in state feedback control systems. The second contribution concerns the new experiments to be done in the IFT of the accepted class of second-order state feedback control systems dedicated to servo systems. The third contribution involves the highlighting of the specific aspects related to the actuator saturation problem proved by the low-cost implementation and the real-time experimental results included. The main advantages of the contributions are the simplification of the experiments and the smooth decrease of the objective function. Thus the local minimum will be reached.

The paper treats the following topics. The controlled processes and the new IFT algorithm dedicated to the accepted class of state feedback control system are presented in Section 2. Next, Section 3 points out original and attractive aspects concerning the actuator saturation problem. A case study concentrated on the state feedback position control of a DC servo system with backlash is described in Section 4. The real-time experimental results validate the IFT algorithm. The conclusions are drawn in Section 5.

2 CONTROLLED PROCESS AND IFT ALGORITHM

The controlled process as part of servo systems is characterized by the following state-space model:

$$\begin{bmatrix} \dot{\alpha} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -\dfrac{1}{T_s} \end{bmatrix} \begin{bmatrix} \alpha \\ \omega \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{K_s}{T_s} \end{bmatrix} u \,, \qquad \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = I_2 \begin{bmatrix} \alpha \\ \omega \end{bmatrix} \tag{1}$$

where α=x_1 is the first state variable usually representing the (angular) position, ω=x_2 is the second state variable usually representing the (angular) speed, u is the control signal, y_1 and y_2 are the controlled outputs, and $\mathbf{I}_2$ is the identity matrix. The two parameters in (1) are K_S>0 which is the process gain, and T_S>0 which stands for the small time constant or the sum of parasitic time constants.

The two transfer functions from u to ω and u to α are $P_{\omega,u}(s)$ and $P_{\alpha,u}(s)$, respectively:

$$P_{\omega,u}(s) = \frac{K_s}{(1+sT_s)}, \, P_{\alpha,u}(s) = \frac{K_s}{s(1+sT_s)} \cdot \tag{2}$$

Therefore the integral component can be observed in (2) when α=x_1 is taken as controlled output. Such situations correspond to positioning systems.

The state feedback control system structure is presented in Figure 1. The dotted connection highlighted is valid only when the experiments specific to IFT are done. That connection is not applied during the normal system operation.

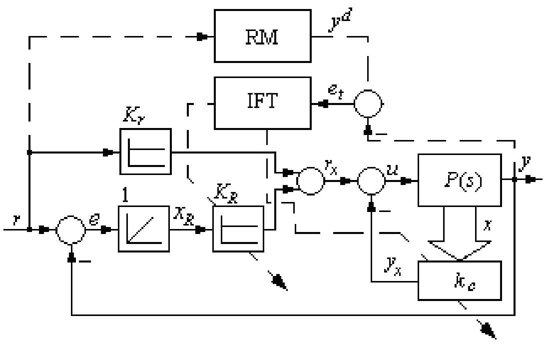

Figure 1: IFT-based state feedback control system structure.

The main variables and blocks illustrated in Figure 1 represent: IFT – the IFT algorithm, RM – the reference model, $\mathbf{x} = [x_1 \quad x_2]^T \in R^2$ – the state vector (T highlights the matrix transposition),

$\mathbf{k}_c = [K_1 \quad K_2]$ – the state feedback gain matrix, $P(s) = P_{\alpha,u}(s)$ – the transfer function of the controlled process when the controlled output is y=x_1, r – the reference input, e=r–y – the control error. The other variables will be presented in the sequel.

If the state feedback gain matrix is regarded as a controller, then use will be made of its parameters to minimize the tracking error e_t between the system output y and the reference model output y^d. Let J be a simple objective function defined over a finite time horizon N:

$$J(\boldsymbol{\rho}) = \frac{1}{2N}\sum_{t=1}^{N}(e_t(\boldsymbol{\rho}))^2, \tag{3}$$

where $\boldsymbol{\rho} \in R^m$ is the parameters vector containing at least the parameters of $\mathbf{k}_c$ and e_t is the tracking error:

$$e_t(\boldsymbol{\rho}) = y(\boldsymbol{\rho}) - y^d. \tag{4}$$

The IFT results (Hjalmarsson et al., 1994, 1998; Pfeiffer et al., 2006) are employed to find the solution ρ^* to the optimization problem

$$\boldsymbol{\rho}^* = \arg\min_{\rho \in SD} J(\boldsymbol{\rho}), \tag{5}$$

where several constraints can be imposed regarding the process and the closed-loop system. One constraint concerns the stability of the system and SD represents the stability domain (Precup et al., 2008).

Solving the optimization problem (5) requires finding the parameters vectors that make the gradient equal to zero:

$$\frac{\partial J}{\partial \boldsymbol{\rho}} = [\frac{\partial J}{\partial \rho_1} \quad \ldots \quad \frac{\partial J}{\partial \rho_m}]^T = 0. \tag{6}$$

Making use of (3) and (4) the equation (6) will be transformed into

$$\frac{1}{N}\sum_{t=1}^{N}\frac{\partial y}{\partial \boldsymbol{\rho}}^T [y(\boldsymbol{\rho}) - y^d] = 0. \tag{7}$$

The partial derivatives $\frac{\partial y}{\partial \rho_i}$ should be calculated to obtain the components of the gradient, $\frac{\partial J}{\partial \rho_i}$, $i = \overline{1, m}$. The new IFT approach to be described as follows will employ specific experiments to obtain those components. Use will be made of the following notation:

$$\alpha' = \frac{\partial \alpha}{\partial \rho_i} \tag{8}$$

to highlight the partial derivative of the variable α taken with respect to ρ_i and obtain the simplicity of the presentation.

The state-space model (1) can be reconsidered by including one additional state variable to the state variable. That variable is x_3=x_R and it corresponds to the integrator inserted into the control system structure. Thus its gain K_R will be subject to IFT as it is shown in Figure 1. The extended state-space model of the process is

$$\begin{aligned} &\begin{bmatrix} \dot{\alpha} \\ \dot{\omega} \\ \dot{x}_R \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -K_s K_1 & -\frac{1}{T_s} - K_s K_2 & K_s K_R \\ -1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \omega \\ x_R \end{bmatrix} + \\ &+ \begin{bmatrix} 0 \\ \frac{K_s}{T_s} K_r \\ 1 \end{bmatrix} r \quad , \\ &\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = I_3 \begin{bmatrix} \alpha \\ \omega \\ x_R \end{bmatrix} \end{aligned} \tag{9}$$

where the parameter K_r is not included in the tuning scheme. Its value is set prior to the application of IFT. One way to choose K_r is to keep a connection between the steady-state value of r and the steady-state value of r_x for which the desired r can be tracked by the steady-state value of y. That value of r_x can be subject to the experimental identification of the state feedback control system.

The preparation of the experimental scheme needed in the calculation of the gradient starts with the reconsideration of the input-output relations specific to the control system structure presented in Figure 1. Observing that generally

$$\begin{aligned} &\mathbf{y} = \mathbf{P}u \\ &u = r_x - \mathbf{k}_c\mathbf{x} = r_x - \mathbf{k}_c\mathbf{y} \text{ for } \mathbf{y} = \mathbf{I}_3\mathbf{x} \end{aligned}, \tag{10}$$

the following relationships hold:

$$\begin{aligned} &r_x = K_r r + K_R x_R, \ u = K_r r + K_R x_R - \\ &- K_1 x_1 - K_2 x_2 = K_r r + \mathbf{K}_c \mathbf{x}_E, \\ &\mathbf{K}_c = [-K_1 \quad -K_2 \quad K_R], \mathbf{x}_E = [x^T \quad x_R]^T \end{aligned} . \tag{11}$$

Next the gradient of y with respect to each parameter can be calculated, where the parameters are the m=3 components of the parameters vector

$$\boldsymbol{\rho} = [K_1 \quad K_2 \quad K_R]^T. \tag{12}$$

Since y and u are functions of ρ it is justified to apply

$$\mathbf{y}' = \mathbf{P}u', \tag{13}$$

leading to

$$u' = \mathbf{K}_c{}'\mathbf{x}_E + \mathbf{K}_c\mathbf{x}_E{}'. \tag{14}$$

In addition, accepting the MIMO formalism suggested in (10), the following relationship can be expressed:

$$u' = \mathbf{K}_c{}'\mathbf{y} + \mathbf{K}_c\mathbf{y}'. \tag{15}$$

Equation (15) is of great importance for the new approach. The first term in the right-hand side of (15), $\mathbf{K}_c{}'\mathbf{y}$, needs to be added to the control signal to obtain the desired experimental scheme. That term contains the unmodified output vector (in the MIMO framework) so the idea is to obtain it from one first initial experiment (Hjalmarsson et. al., 1998). The second term in the right-hand side, $\mathbf{K}_c\mathbf{y}'$, is measured from the control system structure. Therefore the experimental scheme to calculate the gradients results in terms of Figure 2 (without the blocks RM and IFT for the sake of simplicity).

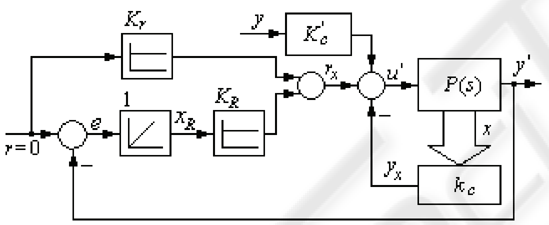

Figure 2: Experimental scheme to calculate the gradients in the IFT-based state feedback control system structure.

The block $\mathbf{K}_c{}'$ in Figure 2 plays the role of filter. It differs from one experiment to another one depending on the actual parameter with respect to which the gradient is computed.

Since the calculation of the gradients has been derived in the MIMO framework, m+1=4 experiments are done with it. The first experiment, referred to also as the normal one, is done with the control system structure presented in Figure 1 in order to measure the controlled output y. The next m=3 experiments, called the gradient experiments, are done with the experimental scheme presented in Figure 2. These experiments are done separately for each parameter in $\mathbf{K}_c$ (defined in (11)) considering the zero values of the other m–1=2 parameters (because their derivatives with respect to the current parameter are zero).

Once the experiments are done the parameters vector must be updated. Newton's algorithm is generally used as one convenient technique which iteratively approaches a zero of a function without knowledge of it's expression. The update law to calculate the next parameters vector $\boldsymbol{\rho}^{i+1}$ is

$$\boldsymbol{\rho}^{i+1} = \boldsymbol{\rho}^i - \gamma_i \mathbf{R}_i^{-1} est[\frac{\partial J}{\partial \boldsymbol{\rho}}(\rho^i)], \tag{16}$$

where i is the index of the current iteration / experiment, γ_i is the step size, $est[\frac{\partial J}{\partial \boldsymbol{\rho}}(\rho^i)]$ is the estimate of the gradient, and the regular matrix $\mathbf{R}_i$ can be the estimate of the Hessian matrix (positive definite) or the identity matrix. The identity matrix is employed when simple implementations are needed.

Making use of all aspects presented before the new IFT algorithm consists of the following steps to be performed per iteration:

Step 1. Do the normal experiment and measure $\mathbf{y}$ based on the control system structure presented in Figure 1. Next do the three gradient experiments making use of the experimental scheme presented in Figure 2 and measure the closed-loop system output that gives the gradient of the controlled output, $\frac{\partial \mathbf{y}}{\partial \boldsymbol{\rho}} = \mathbf{y}'$.

Step 2. Calculate the output of the reference model, $\mathbf{y}^d$, in terms of the control system structure presented in Figure 3.

Step 3. Calculate the estimate of the gradient of the objective function:

$$est[\frac{\partial J}{\partial \boldsymbol{\rho}}(\rho^i)] = \frac{1}{N}\sum_{t=1}^{N} \frac{\partial \mathbf{y}}{\partial \boldsymbol{\rho}}^T [\mathbf{y}(\boldsymbol{\rho}) - \mathbf{y}^d]. \tag{17}$$

Step 4. Calculate the next set of parameters $\boldsymbol{\rho}^{i+1}$ according to the update law (16).

Three aspects can be highlighted with respect to the above presented IFT algorithm. First, prior to the four steps the designer should set the step size, the reference model and the initial controller parameters in the vector ρ^0. Second, the first task of the state feedback controller is to ensure an initially stable control system. The pole placement design can be used with this regard. Third, the estimate of the Hessian matrix should be calculated in the step 3 is it is used as the matrix $\mathbf{R}_i$ in the update law (16) or an additional experiment can be employed with this regard.

3 ACTUATOR SATURATION PROBLEM

In many cases the actuator is characterized by a nonlinear input-output map caused by the actuator saturation. That is a problem because it introduces usually nonlinear behaviours in the evolution of the process. Hence it should be avoided. When making use of the integrator in the controller the actuator saturation problem becomes important since the actuator that enters a deep saturation region requires usually a longer time to re-enter the active region of normal operation.

Analyzing the structure illustrated in Figure 2 and used in the gradient experiments it is clear that when the state vector is injected in the control signal it may cause saturation. Hence the experiment will be prevented from calculating the correct gradients. In the following, an actuator with the active input range varying from −1 to +1 is considered.

One solution to cope with the above mentioned problem is to design the experiment in such a manner that the actuator never enters saturation. For this, the injected quantity must be in the active region of the actuator's input-output static map. The quantity can be scaled to its maximum value from its evolution. That is obtained by dividing every sample to the maximum absolute value from the sample vector. So it is guaranteed that the new quantity to be injected will be within the accepted domain of the actuator input.

It can be shown as follows how the gradient experiments will be influenced. The general case of MIMO IFT will be considered. First, the scaled, added value to the control is defined as

$$z_s(t) = z(t)/M,\ M = \max_{k=1,N} |z(t)| \cdot \qquad (18)$$

Next the gradient of the control signal with respect to the parameters vector, u', can be expressed in (19) accepting a MIMO control loop with the controller transfer function C:

$$u' = C'(r-y) - Cy' = z - Cy' . \qquad (19)$$

Equation (19) is divided by M resulting in the following relationship between the scaled values of the gradients, $u_s' = u'/M$ and $y_s' = y'/M$:

$$u_s' = z/M - Cy_s' . \qquad (20)$$

Concluding, dividing (13) by (18) the result will be

$$y_s' = Pu_s' . \qquad (21)$$

Practically a scaled value of the estimate of the gradient can be obtained making use of the (20) and (21). After the gradient experiments are done the measured values y_s' are multiplied by M. Thus they will give the normal estimate of the gradient to be used in the iterative minimization of the objective function J.

4 CASE STUDY AND REAL-TIME EXPERIMENTS

The validation of the theoretical approaches is done in terms of a case study consisting of a position control, y=α, of a DC servo system with backlash. The experimental setup illustrated in Figure 3 is built starting with the INTECO DC motor laboratory equipment. It makes use of an optical encoder for the angle measurement and a tacho-generator for the measurement of the angular speed. The tacho-generator measurements are very noisy. The speed can also be observed from the angle measurements. The control system performance indices such as settling time and overshoot can be assessed easily.

The process (1) is characterized by the parameters $K_s = 139.88$ and $T_s = 0.9198\,\mathrm{s}$, obtained after experimental identification. The initial parameters vector has been set to $\rho^0 = [0.0132 \quad 0.0126 \quad 0.005]^T$ which has been obtained to stabilize the system.

A constant reference input has been applied, $r = 150\,\mathrm{rad}$. This allows, without any loss of generality, to pre-tune the parameter K_r at the value $K_r = 0.0133$ and drop it of the variables in the optimization problem (5). That value of K_r has been obtained by steady-state calculation as a gain that connects r with α through the steady-state gain of the inner state-feedback loop. The sampling period has been set to 0.01 s. The following reference model has been considered:

$$G_{RM}(s) = 1/(s^2 + 1.5s + 1) . \qquad (22)$$

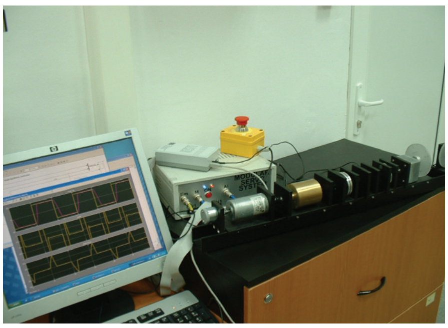

Figure 3: Experimental setup.

Its corresponding pulse transfer function has been obtained for the accepted sampling period. The behaviour of the control system before the application of the IFT algorithm is illustrated in Figure 4.

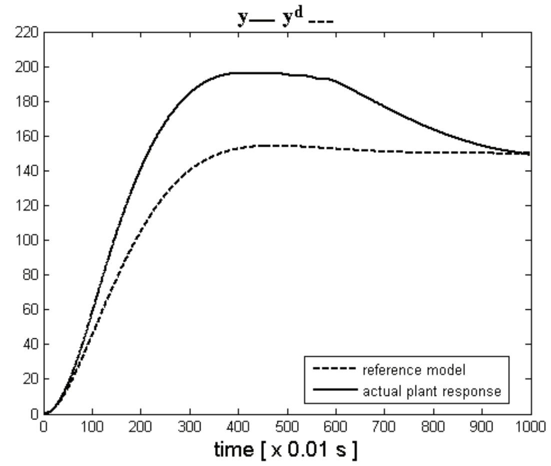

Figure 4: Reference model output and controlled output (position) versus time before IFT.

The IFT algorithm has been applied according to the steps presented in Section 3. The parameters have been set to $\gamma_i = 0.0001$ and $R_i = I_3$. The behaviour of the control system after 12 iterations is presented in Figure 5. The control system performance enhancement is highlighted. It is reflected by smaller overshoot and settling time.

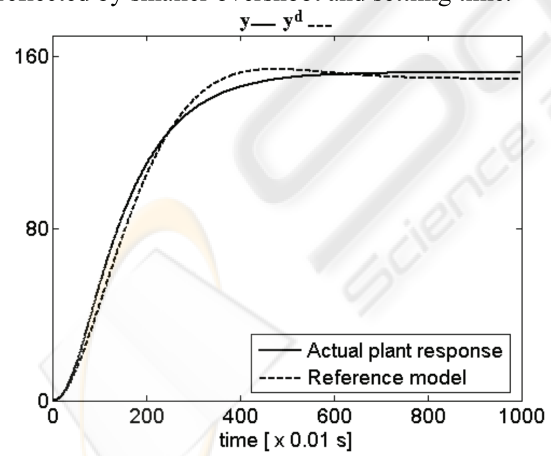

Figure 5: Reference model output and controlled output (position) versus time after IFT.

The variation of the objective function versus the iteration number is illustrated in Figure 6. It shows a good decrease of the objective function and the fact that the number of iterations can be even smaller.

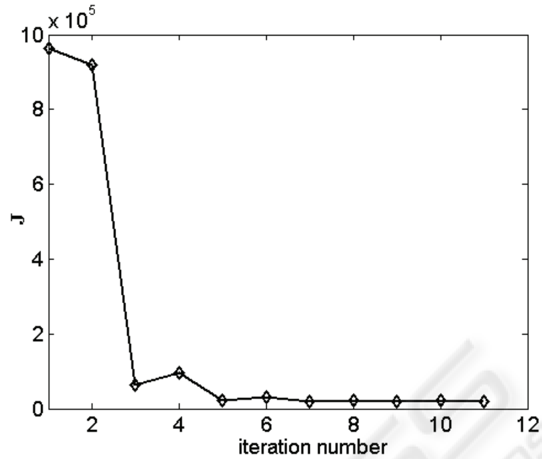

Figure 6: Objective function versus iteration number.

5 CONCLUSIONS

The paper has been presented a new approach to the IFT-based design of state feedback control systems meant for a class of second-order systems with integral component. The new IFT algorithm can be applied without any difficulties to the state feedback control of systems of arbitrary order.

The case study accompanied by real-time experimental results validates the theoretical approaches. The control system designed exhibits better performance indices compared to the situation prior to the application of the IFT algorithm.

The static and kinetic frictions were neglected. They can result in the nonlinearity of the input-output static map $\omega = f(u)$. The idealization considered here simplifies the model to be handled easily because the nonlinearity is not strong.

The first limitation of the proposed IFT approach concerns the tuning of the initial parameters of the controller (grouped in the vector ρ^0). That problem is not simple if nonlinear processes are involved. The second limitation is that the global optimum cannot be guaranteed. Hence only quasi-optimal state feedback control systems can be designed.

The presence of the parameter K_r presented in Figure 1 and Figure 2 is not mandatory because the integrator acts in the direction of error alleviation. So the control system structure can be simplified. However its presence is important because it can influence the initial control error with effects on the convergence of the IFT algorithm.

The future research will be focused on: the consideration of more complex objective functions to include the control signal, the state and output sensitivity functions as well, the generalization to nonlinear processes (Cottenceau et al., 2001; Johanyák and Kovács, 2007; Savaresi et al., 2006; Andrade-Cetto and Thomas, 2008; Giua and Seatzu, 2008; Precup et al., 2008a; Dolgui et al., 2009) including MIMO servo systems, and the mapping of the results from the linear case onto the parameters of the fuzzy controllers in the framework of state feedback fuzzy control systems. The convergence analysis of all IFT algorithms is needed.

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