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Intelligent Proportional Controller Tuned by Virtual Reference Feedback Tuning and Fictitious Reference Iterative Tuning

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Abstract

A comparative study of two mixes of data-driven algorithms is proposed in this paper. The discrete-time second-order model-free control known as an intelligent Proportional (iP) controller is tuned considering Virtual Reference Feedback Tuning (VRFT) and the overall performance of the resulting algorithm iP-VRFT is compared with that of iP controller that is tuned considering Fictitious Reference Feedback Tuning (FRIT), an algorithm that is further referred as iP-FRIT. The comparison is carried out as far as the control systems with these two control algorithms are concerned. The purpose of the comparison study is to determine if VRFT and FRIT optimally determine the iP parameters such that both control system structures perform in the same manner. Both algorithm mixes are experimentally validated on the Tower Crane System equipment.

Keywords: Model-Free Control; Virtual Reference Feedback Tuning; Fictitious Reference Iterative Tuning; tower crane systems

1. Introduction

A comparison study that involves two mixes of three data-driven algorithms is proposed in this paper. The first mix is represented by the discrete-time second-order intelligent Proportional (iP) [1, 2] controller that is combined with Virtual Reference Feedback Tuning (VRFT) [3, 4] to optimally tune the proportional component and the second mix is represented by the same discrete-time second-order iP controller that is combined with Fictitious Reference

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Iterative Tuning (FRIT) [5, 6] also to determine the optimal gain of iP controller. The data-driven combinations presented in this paper will be further referred to as iP-VRFT and iP-FRIT. The theoretical part represented by iP-VRFT and iP-FRIT is validated using experiments on the Tower Crane System (TCS) [7, 8], a laboratory equipment with several nonlinearities, which controls cart position, arm angular position, and payload position. The purpose of this comparison study is to determine if the iP controller is better tuned by mixing it with VRFT or FRIT.

The data-driven algorithms came with the main feature that they use the input/output (I/O) data of the control process in determining the parameters of the controller. Another feature is that they do not require a precise mathematical model of the process, and this feature is very useful when the mathematical model of the process is almost impossible to precisely determine and when it is very complicated.

Model-Free Control (MFC) [1, 2, 8, 9, 10, 11] also known as intelligent controllers is a data-driven algorithm that doesn't make use of the mathematical model of the process and usually has in its componence a classic P or Proportional-Integral-Derivative that exhibits overall very good performances of the control system structure, making it an important data-driven algorithm. Since its initial proposal in the state-of-the-art of automatic control domain, it has been validated on numerous processes like shape memory alloy actuators [2], TCSs [8], twin-rotor aerodynamic systems [9, 12], 3D cranes [13], and networked control in the industrial Internet of Things [14]. VRFT [3, 4, 8] is a data-driven algorithm that computes the parameters of the controller of the control system structure using a primordial set of I/O data that is achieved after an initial open-loop experiment. Next, it determines the controller's optimal parameters. The VRFT algorithm was successfully applied to numerous types of processes including brake-by-wire [3], continuous-time plants [4], TCSs [8], twin-rotor aerodynamic systems [15], and quadrotors [16]. FRIT [5, 6] is part of the data-driven algorithms category it was designed with the purpose to combine the features of VRFT and Iterative Feedback Tuning [17] data-driven algorithms using the I/O data collected after an open-loop experiment and determines iteratively the optimal parameters of the controller. The processes on which FRIT was validated are the servo motor [5], a second order process [6], a broader class of plants [18], TCSs [10, 11], or hexacopter systems [19]. Both iP-VRFT and iP-FRIT algorithms tune the parameters of the proportional component from the iP controller via VRFT and FRIT by solving an optimization problem via the metaheuristic African Vultures Optimization Algorithm (AVOA) [20, 21]. Other mixes of other MFC algorithms versions with the VRFT technique were presented in [8, 15] and other mixes of MFC algorithms versions with FRIT were presented in [10, 11, 18]. Paper [10] proposes to mix the discrete-time first-order iP-integral-derivative (iPID) version of MFC with FRIT with the purpose of improving the performance of iPID control systems via FRIT and the mix is validated using experiments on TCS, and paper [11] proposes to mix the first-order continuous-time iPI with FRIT to achieve the same purpose. The paper's novelty is that it makes a comparative study of data-driven discrete-time second-order iP-VRFT and iP-FRIT algorithms considering the minimum value of a performance index for optimal tuning.

The differences of the proposed iP-FRIT algorithms in the current paper and the iPID-FRIT mix in [10] are (i), (ii) and (iii): (i) the current paper uses a discrete-time second-order version of the MFC algorithm while in [10] a first-order discrete-time version is used; (ii) here, the iP version of MFC is used while in [10] the iPID version is used; (iii) the optimal parameters resulted by mixing MFC with FRIT are computed via SMA algorithm while in [10] the optimal parameters are generated via AVOA algorithm. The differences between the proposed data-driven iP-FRIT algorithms in this paper and the iPI-FRIT mix in [11] are (1) and (2): (1) the current paper uses a discrete-time second-order version of the MFC algorithm while in [11] a first order continuous-time version is used; (2) here, the iP version of MFC is used while in [11] the iPI version is used. All three mixed versions of data-driven MFC and FRIT algorithms ensure that in all cases the data-driven FRIT algorithms manage to improve the performance of the control loop by adjusting properly the parameters of the MFC algorithm.

Next, the paper is organized as: in the second section the mathematical model of the TCS laboratory equipment is detailed, in the third section the data-driven iP-VRFT and iP-FRIT algorithms are presented, in the fourth section the experimental results are highlighted and in the fifth section the conclusions are pointed out.

2. The TCS Process

The experimental validation of the proposed discrete-time second-order iP-VRFT and iP-FRIT algorithms is made on the TCS, a three-degrees-of-freedom nonlinear laboratory equipment that ensures the control of cart position, arm angular position, and payload position. The mathematical model that characterizes the behavior of the laboratory equipment was elaborated and is detailed in [8] and contains the variables: the first control signal is denoted with $u_1 \in [-1, 1]$ expressed in Pulse Width Modulation (PWM) duty cycle of the first DC motor of the first controlled output of the TCS is denoted with $y_1(m) = x_3(m) \in [-0.25, 0.25]$ of the cart position, the second control signal is denoted with $u_2 \in [-1, 1]$ expressed in PWM duty cycle of the DC motor to control the second output of the TCS is denoted with $y_2(\text{rad}) = x_4(\text{rad}) \in [-1.57, 1.57]$ of the arm angular position, and the third control signal is denoted with $u_3 \in [-1, 1]$ expressed in PWM duty cycle of the DC motor to control the third output of the TCS is denoted with $y_3(\text{m}) = x_9(\text{m}) \in [-0.4, 0.4]$ of the lift line position (describes the position of the payload) [7, 8, 10, 11, 21].

The nonlinearities of the actuators that set the TCS equipment in motion are highlighted through its very accurate mathematical model described in [8], where both TCS's mathematical model along with its all constants can be found in [8].

3. The Data-Driven iP-VRFT and iP-FRIT Algorithms

3.1. The intelligent Proportional (iP) controllers

The discrete-time second-order iP controller is designed considering the second-order ultra-local model

$$y_k = 2y_{k-1} - y_{k-2} + \alpha\, u_{k-1} + F_{k-1}, \tag{1}$$

where $y_k \in \mathbf{R}$ is the controlled output, $u_k \in \mathbf{R}$ is the control input, $\alpha \in \mathbf{R}$ is a positive user-chosen constant recommended to be chosen to ensure that $\Delta y_{k+1} = y_{k+1} - y_k$ and αu_k are in the same order of magnitude, and $F_k \in \mathbf{R}$ gathers the unmodeled dynamics and unmodeled disturbances [1, 2, 8, 10, 11, 15].

The control law specific to discrete-time second-order iP controllers is

$$u_k = \alpha^{-1}(-\hat{F}_k + y^*_{k+1} - y^*_k - K\varepsilon_k), \tag{2}$$

where $y^*_k \in \mathbf{R}$ is the reference input or the set-point, which can also be applied as a reference trajectory, $K \in \mathbf{R}$ is the P gain, $\varepsilon_k \in \mathbf{R}$ is the control error

$$\varepsilon_k = y^*_k - y_k, \tag{3}$$

$\hat{F}_k \in \mathbf{R}$ is the estimate of F_k, which is obtained using the I/O online data, their difference is considered to be a negligible random disturbance δ_k

$$\delta_k = F_k - \hat{F}_k \cong 0, \tag{4}$$

and $\hat{F}_k$ is computed in terms of [1, 2, 8, 10, 11, 15]

$$\hat{F}_k = y_k - 2y_{k-1} + y_{k-1} - \alpha\, u_{k-1}. \tag{5}$$

The dynamics of the control system structure with discrete-time second-order iP controller is computed by inserting the controlled input from (2) in the second-order ultra-local model (1). Therefore, the dynamics equation is

$$y_k = y^*_{k-2} - 2y^*_{k-1} + y^*_k - y_{k-2} + 2y_{k-1} - y_{k-2} - K\varepsilon_{k-1} + F_{k-1} - \hat{F}_{k-1}. \tag{6}$$

The control error dynamics of this control system structure results as follows by substituting δ_k from (4) in (6):

$$\varepsilon_k - (2+K)\varepsilon_{k-1} + \varepsilon_{k-2} = -\delta_{k-1}. \quad (7)$$

If the roots of the characteristic polynomial of the control error dynamics (7) are inside the unit circle then the control system structure with iP controller will be stable [1, 2, 8, 10, 11, 15].

3.2. The intelligent Proportional–Virtual Reference Feedback Tuning (iP-VRFT) algorithms

The purpose of mixing the discrete-time second-order MFC algorithm in the iP version with VRFT is to determine the optimal parameter of iP controller without using the mathematical model of the process. A set of I/O data generated after applying a signal rich in spectrum and frequency to the open-loop control process is needed for the iP-VRFT algorithm.

The equivalent control law used in the discrete-time second-order iP-VRFT algorithm is obtained after substituting the control error defined in (3) and the estimate of $\hat{F}_k$ taken from (5) in the iP control law given in (2):

$$u_k = \alpha^{-1}(\alpha u_{k-1} + y^*_{k-1} - 2y^*_k + y^*_{k+1} - y_{k-2} + 2y_{k-1} - y_k - K(y^*_k - y_k)), \quad (8)$$

after adding and subtracting the one step behind the reference trajectory y^*_{k-1} and the controlled output y_k, the control law in (8) will be rewritten as follows using (3) [1, 2, 8, 10, 11, 15]:

$$u_k = u_{k-1} + \alpha^{-1}(-(1+K)\varepsilon_k + \varepsilon_{k-1} - y^*_k + y^*_{k+1} - y_{k-2} + 3y_{k-1} - 2y_k). \quad (9)$$

The recurrent form for the discrete-time second-order iP-VRFT algorithm is $u_k = g(\varepsilon_k, \varepsilon_{k-1}, u_{k-1}, \chi, \vartheta)$, where $\chi = K$ is the tunable parameter vector (a scalar in this controller case), $\vartheta \in \mathbf{R}^6$, is the non-tunable parameter vector defined as $\vartheta = [\alpha \ y^{*T}_k \ y^{*\,T}_{k+1} \ y^T_{k-2} \ y^T_{k-1} \ y^T_k]^T = [\vartheta(1) \ \vartheta(2) \ \theta(3) \ \vartheta(4) \ \vartheta(5) \ \vartheta(6)]^T$, and g is a nonlinear scalar function of vector variable, which is expressed as

$$\begin{aligned} & g:\mathbf{R}^{10} \to \mathbf{R},\ g(\varepsilon_k, \varepsilon_{k-1}, u_{k-1}, \chi, \vartheta) \\ & = u_{k-1} + \vartheta(1)^{-1}[-(1+K)\varepsilon_k + \varepsilon_{k-1} - \theta(2) + \vartheta(3) - \vartheta(4) + 3\vartheta(5) - 2\vartheta(6)]. \end{aligned} \quad (10)$$

The combination of discrete-time second-order iP-VRFT is successfully ensured if the control error ε_k and the reference trajectory y^*_k of iP are linked with the virtual error $\bar{\varepsilon}_k$ and the virtual reference input $\bar{y}^*_k$ specific to VRFT where the control law in (10) can be rewritten $u_{\chi k} = C_\chi(\chi, u_{\chi k-1}, \ldots, u_{\chi k-n_{uc}}, \varepsilon_k, \ldots, \varepsilon_{k-n_{ec}})$, where $u_{\chi k} \in \mathbf{R}$ is generated by the VRFT algorithm, $\mathbf{C}_\chi : \mathbf{R}^{n_{uc}+n_{ec}+2} \to \mathbf{R}^n$, n_{uc} and n_{ec} are the maximum known delay orders related to the control input vector, and $\boldsymbol{\theta} = [\chi \ \vartheta^T]^T$. The parameters of the iP controller are determined using VRFT considering the above links between the parameters of the VRFT. The objective function of the general model reference tracking problem is [1, 2, 3, 4, 8, 10, 11, 15]

$$J_{MR}(\chi) = \sum_{k=1}^{N} (y_{\chi k} - y^*_k)^2, \quad (11)$$

where N gathers the total number of samples, $y^*_k \in \mathbf{R}$ is the reference input or the set-point also specified in (2), which in this algorithm is the reference model output, $y_{\chi k} = f(y_{\chi k}, \ldots, y_{\chi k-n_{yp}}, u_{\chi k}, \ldots, y_{\chi k-n_{up}})$ is the controlled output of the nonlinear process, where $f:\mathbf{R}^{n_{yp}+n_{up}+2}\to\mathbf{R}$ is an unknown nonlinear scalar function of vector variable, n_{yp} and n_{up} are the maximum known delay orders related to the controlled output and the control input. The reference model output $y_k^*=m_{RM}(y_{k-1}^*,\ldots,y_{k-n_{ym}}^*,\bar{y}_{k-1}^*,\ldots,\bar{y}_{k-n_{rm}}^*)$ is generated considering a nonlinear reference element m_{RM} of n_{ym} and n_{y^*m} orders chosen by the practitioner.

The VRFT algorithm computes the virtual reference input as

$$\bar{y}_k^* = m_{RM}{}^{-1} y_k, \tag{12}$$

such that the reference model and the output of the control system will have similar trajectories. The discrete-time second-order iP-VRFT algorithm determines the optimal parameters when [1, 2, 3, 4, 8, 10, 11, 15]

$$J_{VRFT}(\chi)=\frac{1}{N}\sum_{k=1}^{N}(\mathbf{C}_\chi(\chi,u_{\chi k-1},\bar{\varepsilon}_k)-u_{\chi k})^2 \tag{13}$$

is minimized and if the objective functions $J_{MR}(\chi)$ in (11) and $J_{VRFT}(\chi)$ in (13) have similar values, and where $\bar{\varepsilon}_k=\bar{y}_k^*-y_k$ is the virtual control error [1, 2, 3, 4, 8, 10, 11, 15].

The schematic block diagram of the discrete-time second-order iP-VRFT algorithm is depicted in Fig. 1 a).

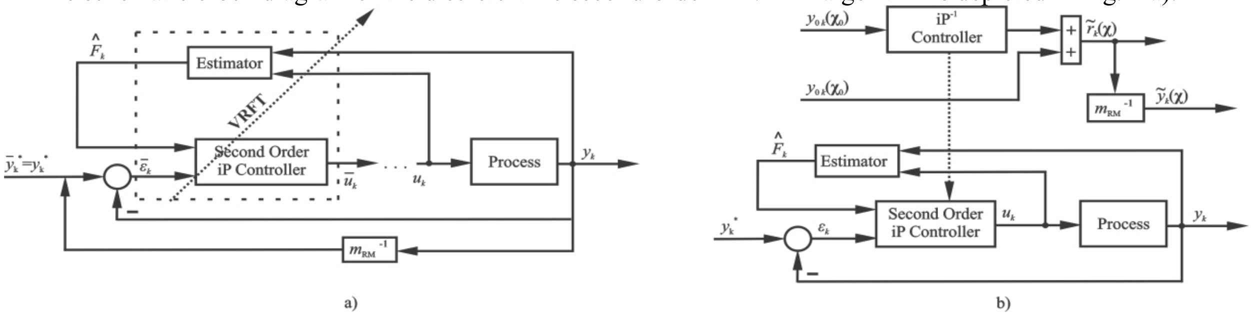

Fig. 1. a) The control system structure with the iP-VRFT algorithm. b) The control system structure with iP-FRIT algorithm

3.3. The intelligent Proportional–Fictitious Reference Feedback Tuning (iP-FRIT) algorithms

The purpose of mixing the discrete-time second-order MFC algorithm in the iP version with FRIT is to iteratively improve the parameter of the iP controller without using the mathematical model of the process. In the case of the discrete-time second-order iP-FRIT algorithm, the set of I/O data is obtained after an initial open-loop experiment.

In the case of the iP-FRIT algorithm, the optimal parameter of the iP controllers is determined when

$$J_{FRIT}(\chi)=\sum_{k=1}^{N}[y_{0k}(\chi_0)-\tilde{y}_{\chi k}(\chi)]^2 \tag{14}$$

is minimized, where $\chi = K$ is the tunable parameter vector (a scalar in this controller case), $y_{0k}(\chi_0)$ is the controlled output obtained after the initial closed-loop experiment, χ_0 is the initial parameter of iP controller, and $\tilde{y}_{\chi k}(\chi)$ is the fictitious reference model output and is determined offline [5, 6, 10, 11]

$$\tilde{y}_{\chi k}(\chi)=m_{RM}{}^{-1}\tilde{y}_k^*(\chi), \tag{15}$$

where $\tilde{y}_k^*(\chi)$ is the fictitious reference input also known as the virtual set-point

$$\tilde{y}_k^*(\chi) = C(\chi)^{-1} u_{0k}(\chi_0) + y_0(\chi_0), \tag{16}$$

the signal $u_{0k}(\chi_0)$ is collected after the initial experiment, and $C(\chi)^{-1}$ is the inverse transfer function of the P component. The minimization of the objective function in (14) is equivalent to the minimization of the sum of $(y_k(\chi) - m_{RM}{}^{-1} y_k^*)^2$ to guarantee model reference tracking [5, 6, 10, 11].

The schematic block diagram of the discrete-time second-order iP-FRIT algorithm is depicted in Fig. 1 b).

4. Experimental Setup

Both discrete-time second-order iP-VRFT and iP-FRIT algorithms are experimental validated on the TCS. The performance of both algorithms is compared through the performance index

$$J_{\varepsilon,u}(\chi_\Diamond) = \sum_{k=1}^{N} [\varepsilon_{1\,k}^2(\chi_{\Diamond 1}) + \varepsilon_{2\,k}^2(\chi_{\Diamond 2}) + \varepsilon_{3\,k}^2(\chi_{\Diamond 3})], \tag{17}$$

where subscript 1 is used for cart position, subscript 2 for arm angular position, and subscript 3 for payload position, and $\Diamond = \text{iP} - \text{VRFT}$ or $\Diamond = \text{iP} - \text{FRIT}$. In the experiments zero initial conditions are considered, the time horizon is set to 70 s, the sampling period is $T_s = 0.01 s$, the number of samples is $N = 7000$ and no additive disturbances are applied. The reference trajectory of control system structures is [8]

$$\begin{aligned}
&y_{\tilde{1}\,k} = 0.15 \textit{ if } k \in [0, 20/T_s], 0.1 \text{ if } k \in (20/T_s, 35/T_s], -0.05 \text{ if } k \in (35/T_s, 50/T_s], 0 \text{ if } k \in (50/T_s, 70/T_s],\\
&y_{\tilde{2}\,k} = 0 \textit{ if } k \in [0, 5/T_s], 0.15 \text{if } k \in (5/T_s, 25/T_s], -0.15 \text{ if } k \in (25/T_s, 40/T_s], 0 \text{ if } k \in (40/T_s, 70/T_s],\\
&y_{\tilde{3}\,k} = 0 \textit{if } k \in [0, 15/T_s], 0.1 \text{ if } k \in (15/T_s, 30/T_s], -0.05 \text{ if } k \in (30/T_s, 45/T_s], 0 \text{ if } k \in (45/T_s, 70/T_s],
\end{aligned} \tag{18}$$

and is filtered through

$$H_{y_{\tilde{1}\,k}} = 0.04877/(z - 0.9512), H_{y_{\tilde{2}\,k}} = 0.0465/(z - 0.9535), H_{y_{\tilde{3}\,k}} = 0.03278/(z - 0.9672), \tag{19}$$

therefore, the reference trajectory used as input in the control system structure is the result of filtering the signals from (18) through filters in (19)

$$y_{1k}^* = y_{\tilde{1}\,k} H_{y_{\tilde{1}\,k}},\ y_{2k}^* = y_{\tilde{2}\,k} H_{y_{\tilde{2}\,k}},\ y_{3k}^* = y_{\tilde{3}\,k} H_{y_{\tilde{3}\,k}}. \tag{20}$$

The reference models in iP-VRFT and iP-FRIT algorithms have the discrete-time transfer functions

$$m_{RM\,1} = \frac{5.813 \cdot 10^{-5} + 5.583 \cdot 10^{-5}}{z^2 - 1.886z + 0.886}, m_{RM\,2} = \frac{1.122 \cdot 10^{-4} + 1.12 \cdot 10^{-4}}{z^2 - 1.993z + 0.993}, m_{RM\,3} = \frac{6.399 \cdot 10^{-5} + 6.19 \cdot 10^{-5}}{z^2 - 1.905z + 0.9054}. \tag{21}$$

The reference models in (21) are used in computing the virtual reference input in (12) of the iP-VRFT algorithm and the fictitious reference output in (15) of the iP-FRIT algorithm. The value of the parameter chosen by the practitioner is set $\alpha = 0.0015$ and the same value is used for the iP-VRFT and iP-FRIT algorithms for all three degrees of freedom of the TCS laboratory equipment. In the case of the iP-FRIT algorithm, the initial parameters are chosen by the practitioner as follows to fulfill the constraints concerning (7) that guarantee the stability of the control system structure with the iP controller:

$$\chi_{0\,\text{iP}_1}^* = K_{0\,\text{iP}_1}^* = -0.75,\ \chi_{0\,\text{iP}_2}^* = K_{0\,\text{iP}_2}^* = -0.89,\ \chi_{0\,\text{iP}_3}^* = K_{0\,\text{iP}_3}^* = -0.8. \tag{22}$$

The optimal parameters of iP-VRFT and iP-FRIT are computed by minimizing the objective functions in (13) for the iP-VRFT algorithm and from (14) for the iP-FRIT algorithm by making use of AVOA algorithms by fulfilling the constraint in (7) that guarantees the stability of the control system structure with iP controller obtaining

$$\begin{aligned}&\chi^*_{\mathrm{iP-VRFT}_1}=K^*_{\mathrm{iP-VRFT}_1}=-0.7799,\ \chi^*_{\mathrm{iP-VRFT}_2}=K^*_{\mathrm{iP-VRFT}_2}=-0.8981,\ \chi^*_{\mathrm{iP-VRFT}_3}=K^*_{\mathrm{iP-VRFT}_3}=-0.9750,\\&\chi^*_{\mathrm{iP-FRIT}_1}=K^*_{\mathrm{iP-FRIT}_1}=-0.7591,\ \chi^*_{\mathrm{iP-FRIT}_2}=K^*_{\mathrm{iP-FRIT}_2}=-0.9218,\ \chi^*_{\mathrm{iP-FRIT}_3}=K^*_{\mathrm{iP-FRIT}_3}=-0.9801.\end{aligned} \tag{23}$$

The AVOA setup to determine the optimal parameter of the discrete-time second-order iP-VRFT and iP-FRIT algorithms are the total number of vultures or agents set to 8, the maximum number of iterations is set to 8, $\alpha_{AVOA}=0.8$ and $\beta_{AVOA}=0.2$ parameters that are involved in the calculation of the probability of choosing the selected agents to move the other agents towards one of the best solutions in each group and $P_1 = 0.6$, $P_2 = 0.4$, $P_3 = 0.6$ – thresholds in the exploration and exploitation phases. The detailed mechanism of the AVOA is presented in [20, 21].

The results obtained by applying discrete-time second-order iP-VRFT and iP-FRIT algorithms are depicted in Fig. 2 a) for controlling the cart position, in Fig. 2 b) for controlling the arm angular position, and in Fig. 2 c) for controlling the payload position of the TCS laboratory equipment.

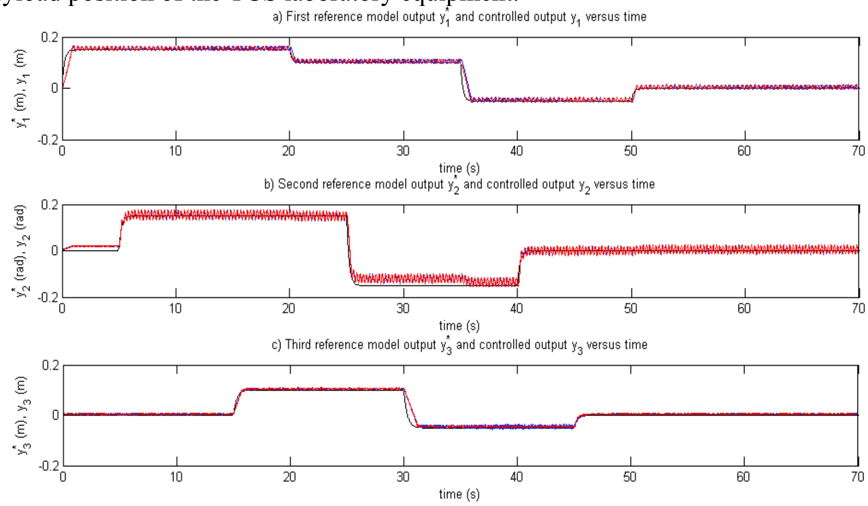

Fig. 2. The output results of the control system structure with iP-VRFT (blue) and iP-FRIT (red) for a) cart position, b) arm angular position, and c) payload position

The average value of the performance index defined in (17) for the iP-VRFT algorithm is $J_{\varepsilon,u}(\chi_\Diamond)=3.5355$ and for the iP-FRIT algorithm is $J_{\varepsilon,u}(\chi_\Diamond)=3.3645$. The variances of the performance index for the iP-VRFT algorithm is $J_{\varepsilon,u}(\chi_\Diamond)=3.1393\cdot10^{-5}$ and for the iP-FRIT algorithm is $J_{\varepsilon,u}(\chi_\Diamond)=4.3112\cdot10^{-5}$. These values are obtained after ten experiments to average the random disturbances that can occur anytime when the experiments are conducted. Considering the performance index values and the experimental results depicted in Fig. 2 it can be affirmed that the discrete-time second-order iP-VRFT and iP-FRIT algorithms have similar performances, and a small advantage has the iP-FRIT algorithm since it computes iteratively the parameter of the controller.

5. Conclusions

A comparison study that involves a mix of three data-driven algorithms was done in the current paper by combining the second-order iP controller known as the data-driven MFC algorithm with data-driven VRFT and data-driven FRIT. The comparison study was proposed to determine which algorithm performs better.

The purpose of the mix in the current paper was to determine optimally the parameters of the iP controller. Both discrete-time second-order iP-VRFT and iP-FRIT algorithms have been successfully validated through experiments on the TCS laboratory equipment. The paper contributions are the experimental validations and the comparison study of discrete-time second-order version of iP-VRFT and iP-FRIT tuned via SMA on TCS. The future work will involve validating the discrete-time second-order iP-VRFT and iP-FRIT algorithms on other laboratory equipment's as the active suspension laboratory equipment, and another goal is to combine different data-driven algorithms to obtain better control performance, and comparing the controllers proposed in this paper with those in [8].

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References

[1] Fliess M, Join C. Model-free Control, *Int J Control*; 2013, 86, (12), p. 2228–2252.
[2] Gédouin PA, Delaleau E, Bourgeot JM, Join C, Chirani SA, Calloch S. Experimental Comparison of Classical PID and Model-free Control: Position Control of a Shape Memory Alloy Active Spring, *Control Eng Pract*; 2011, 19, (5), 433-441.
[3] Formentin S, Campi MC, Care A, Savaresi SM. Deterministic Continuous-time Virtual Reference Feedback Tuning (VRFT) with Application to PID Design. *Syst Control Lett*; 2019, 127, p. 25–34.
[4] Lecchini A, Campi MC, Savaresi SM. Sensitivity shaping via virtual reference feedback tuning. In *Proc 40th Conf Dec Control*, Orlando, FL, USA; 2001, p. 750–755.
[5] Soma S, Kaneko O, Fujii T. A New Method of Controller Parameter Tuning Based on Input-Output Data – Fictitious Reference Iterative Tuning (FRIT). *IFAC Proc Vol*; 2004, 37, (12), p. 789–794.
[6] Kaneko O. Data-Driven Controller Tuning: FRIT Approach. *IFAC Proc Vol*; 2013, 47, (11), p. 326–336.
[7] Tower Crane, User's Manual. Krakow, Poland: *Inteco Ltd.*; 2012.
[8] Precup RE, Roman RC, Safaei A. Data-driven Model-free Controllers, 1st Ed., *CRC Press, Taylor & Francis*, Boca Raton, FL; 2021.
[9] Roman RC, Precup RE, David, RC. Second order intelligent proportional-integral fuzzy control of twin rotor aerodynamic systems. *Proc Comput Sci*; 2018, 139, p. 372–380.
[10] Roman RC, Precup RE, Petriu EM, Muntyan M. Fictitious Reference Iterative Tuning of Discrete-Time Model-Free Control for Tower Crane Systems, *Stud Informat Control*; 2023, 32, (1), p. 5–14.
[11] Roman RC, Precup RE, Petriu E M, Muntyan M, Hedrea EL. Fictitious Reference Iterative Tuning of Intelligent Proportional Integral Controllers for Tower Crane Systems. In Proc. *31st Mediter Conf Control Autom*, Limassol, Cyprus; 2023, p. 1–7.
[12] Fliess M, Join C. An Alternative to Proportional-Integral and Proportional-Integral-Derivative Regulators: Intelligent Proportional-Derivative Regulators, *Int J Robust Nonl Control*; 2022, 32, (18), p. 9612–9524.
[13] Precup RE, Roman RC, Hedrea EL, Petriu EM, Bojan-Dragos CA. Data-driven Model-free Sliding Mode and Fuzzy Control with Experimental Validation, *Int J Comput Communic Control*; 2021, 16, (1), p. 1–17.
[14] Join C, Fliess M, Chaxel F. Model-free Control as a Service in the Industrial Internet of Things: Packet Loss and Latency Issues via Preliminary Experiments. In Proc. *5th Int Conf Control Fault-Toler Syst*, Saint-Raphael, France; 2021, p. 299–306.
[15] Roman RC, Radac MB, Precup RE. Mixed MFC-VRFT Approach for a Multivariable Aerodynamic System Position Control. In Proc. *2016 IEEE Int Conf Syst Man Cybern*, Budapest, Hungary; 2016, p. 002615–002620.
[16] Panizza P, Invernizzi D, Riccardi F, Formentin S, Lovera M. Data-Driven Attitude Control Law Design for a Variable-Pitch Quadrotor. In Proc. *2016 Amer Control Conf*, Boston, MA, USA; 2016, p. 4434–4439.
[17] Hjalmarsson H, Gevers M., Gunnarsson S, Lequin O. Iterative Feedback Tuning: Theory and Applications, *IEEE Control Syst Mag*; 1998, 18, (4), p. 24–41.
[18] Sato T, Miyake S, Kaneko O. An Extension of Intelligent PID Control System to I-PD Typed Control System and Parameter Tuning by FRIT, *IEEJ Trans Electron Informat Syst*; 2022, 142, 3, p. 299–306.
[19] Latt ZKK, Kaneko O. Controller Parameter Tuning of a Hexacopter with Fictitious Reference Iterative Tuning. In Proc. *2019 SICE Int Symp Control Syst*, Kumamoto, Japan; 2019, p. 96–101.
[20] Abdollahzadeh B, Gharehchopogh FS, Mirjalili S. African Vultures Optimization Algorithm: A New Nature-inspired Metaheuristic Algorithm for Global Optimization Problems, *Comput Ind Eng*; 2021, 158, p. 1–37.
[21] Precup RE, Hedrea EL, Roman RC, Petriu EM, Bojan-Dragos CA, Szedlak-Stinean AI, Paulescu FC. AVOA-Based Tuning of Low-cost Fuzzy Controllers for Tower Crane Systems. In Proc. *2022 IEEE Int Conf Fuzzy Syst*, Padua, Italy; 2022, p. 1–8.