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Fictitious Reference Iterative Tuning of Internal Model Controllers for Nonlinear Systems with Hysteresis*

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***Abstract*— In this paper, we propose a data-driven tuning method of internal model controllers (which is abbreviated as IMC) for nonlinear systems with hysteresis. We utilize fictitious reference iterative tuning (which is abbreviated as FRIT), which yields the desired controller parameter with only one-shot experimental data without any mathematical models of a plant, to obtain the desired parameter of the IMC in which a mathematical model consisting of not only a dynamical linear part but also static hysteresis one is implemented. As a result, our proposed method enables us to obtain not only a desirable controller but also a mathematical model of the nonlinear system with hysteresis.**

I. INTRODUCTION

Most of actual plants to be controlled in practical applications are nonlinear dynamical systems. There are many cases where it is not appropriate to approximate a nonlinear system as a linear dynamical system due to its inherent characteristics related to strong nonlinearity. Particularly, hysteresis is known as one of the nonlinear characteristics which cannot be well-approximated by linear systems. In addition, hysteresis reflects one of the common features on actuators used in many control applications, so it is important to address such a nonlinearity from the practical points of view.

To address such a system, this paper extends the internal model control (IMC) [1] architecture to nonlinear systems. It is well known that the IMC has a simple structure which works to decrease the error between the output of the actual plant and the output generated by the internal model included in the controller. It is considered that such a simplicity on the control architecture is useful to control of a class of nonlinear systems like hysteresis. On the other hand, it is also difficult to figure out hysteresis as a mathematical model. This implies that the strategy by which experimental data can be utilized for controller design or tuning without a mathematical model is to be expected as one of the rational approaches to the IMC for a nonlinear system with hysteresis.

Thus, in addition to expansion of IMC to nonlinear systems with hysteresis, this paper also proposes a data-driven approach to the IMC for nonlinear hysteresis systems without mathematical models. Here, the data-driven approach is to design a controller or tune a parameter of the controller with the direct use of the data without mathematical models. As representative works in this framework, Iterative Feedback Tuning (IFT) in [2], Virtual Reference Iterative Tuning (VRFT) in [3], the non-iterative version of correlation based tuning in [4] and the Fictitious Reference Iterative Tuning (FRIT) in [5] and [6] were proposed and studied. Among them, IFT is the most rational approach because the cost function to be minimized in IFT directly represents the purpose of controller tuning. However, IFT requires many experiments, which is a crucial drawback from the practical points of view. The latter three methods enables us to obtain the desired parameter with only one-shot experiment. Here, we take the FRIT approach which is intuitively understandable since the output is focused in this method for off-line minimization of IMC.

Moreover, we require a parameterized mathematical model as the internal model to be implemented in the IMC. As an appropriate parameterization, several hysteresis models were proposed, such as [7] and [8]. A hysteresis model introduced in [7], which is called a heuristic recurrent neural network (HRNN), is one of effective models capable of designing a good hysteresis model. However, since a HRNN model consists of as many parameters as at least 20-30 parameters, it might take much time and make inferior control performance to optimize the cost function in FRIT for IMC. To cope with this problem, another hysteresis model is proposed in [8] by Wakasa *et al*. This model is easily handled because it is characterized with only three parameters. Thus, we implement the parameterized model proposed in [8] as the internal model for nonlinear system with hysteresis.

Moreover, in the case where the internal model completely reflects the dynamics of the actual plant, implementing the model of a plant to IMC yields the desired tracking property. Conversely, in the case in which we do not know a mathematical model of a plant, the achievement of the desired output by some sort of method based on the direct use of the data, like FRIT, enables us to identify the plant as the internal mathematical model in IMC. Thus, our proposed method with data-driven tuning FRIT can be regarded as the way of not only attainment of a controller but also identification of a mathematical model. It is effective and useful to perform such a simultaneous attainment of controller and model from the practical points of view.

This paper is organized as follows. In section II, we give the problem formulation. In section III, we give some required preliminaries. In section IV, we explain how FRIT

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is embedded into IMC for the hysteresis model. In section V, we show that performing FRIT leads to obtain the optimal controller and to identify the mathematical model of a plant by using an illustrative numerical example. In section VI, we give concluding remarks.

[Notation]: Let $\mathbb{R}$ denote the set of real numbers. In terms of the enhancement of the readability, we often omit the notation 's' from a transfer function $G(s)$ if it is clear from the context. In addition, the output of a transfer function G with respect to the input u is denoted with $y = Gu$ with enhancement of the readability. Together the sampling period δ, we prepare the norm defined by $||w||_{(N,\Delta)} := \sqrt{\frac{1}{N}\sum_{i=0}^{N}(w(\Delta i))^2}$ for the sampled time series of w from $t = 0$ to $t = N\Delta$.

II. PRELIMINARIES

In this section, we give brief reviews on FRIT for linear time-invariant case and hysteresis model.

A. Problem Formulation

In Fig. 1, we illustrate the conventional control system with a tunable controller. This paper assume that a plant G is single-input and single output, linear, time invariant, and minimum phase. We also assume that G is unknown while the structure of G is known. In the following, Let G_n denote a nominal model of a plant.

A feedback controller $C(\rho)$ is with a tunable parameter vector ρ. For, example, $C(\rho)$ is parameterized as

$$C(\rho) = \frac{\rho_1 s^n + \rho_2 s^{n-1} + \cdots + \rho_n s + 1}{\rho_{n+1} s^n + \rho_{n+2} s^{n-1} + \cdots + \rho_{2n} s + \rho_{2n+1}}$$

with the parameter vector $\rho := [\rho_1\ \rho_2\ \cdots\ \rho_{2n}\ \rho_{2n+1}]$. The closed loop can be also regarded as the function of ρ, so we denote

$$T(\rho) := \frac{G}{1 + GC(\rho)}$$

as the transfer function from r to y.

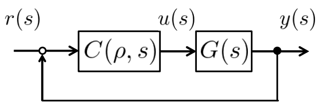

Fig. 1. A closed loop control system

We assume that $C(\rho_{\text{ini}})$ with the initial parameter ρ_{ini} tentatively stabilizes the closed loop so as to obtain the bounded input $u_{\text{ini}} := u(\rho_{\text{ini}})$ and the bounded output $y_{\text{ini}} := y(\rho_{\text{ini}})$. We are also given a desired property as the reference model from r to y as T_d.

Under these settings, the purpose of this paper is to propose the data-driven tuning method for the optimal parameter such that

$$J(\rho) = ||y(\rho_{\text{ini}}) - T_d\tilde{r}(\rho)||^2_{(N,\Delta)}$$

is minimized with only using the data u_{ini} and y_{ini}.

B. Fictitious Reference Iterative Tuning (FRIT) linear time-invariant systems

We give a brief review of FRIT based on the reference [5]. Then, the purpose of the tuning of a controller is that the control system yields the desired output. First, perform an experiment on the closed loop system with $C(\rho_{\text{ini}})$ to obtain y_{ini} and u_{ini}. Then we compute the fictitious reference signal $\tilde{r}(\rho)$, which was originally proposed in [9], as follows,

$$\tilde{r}(\rho) = C(\rho)^{-1}u_{\text{ini}} + y_{\text{ini}}. \tag{1}$$

We introduce the error signal

$$\tilde{e}(\rho) = y_{\text{ini}} - T_d\tilde{r}(\rho).$$

To construct the cost function

$$J_F(\rho) = \sum_{t=0}^{N}(\tilde{e}(\rho))^2. \tag{2}$$

Then, the task of FRIT is to find the optimal parameter

$$\tilde{\rho} := \arg\ \min_{\rho} J_F(\rho).$$

Finally, implement $\tilde{\rho}$ to the controller. Note that (9) with the fictitious reference $\tilde{r}(\rho)$ in (1) requires only u_{ini} and y_{ini}. This means that the minimization of (9) can be performed off-line by using only one-shot experimental data. The relationship between the minimization of (9) and that of (1) can be given by rewriting the cost function $J_F(\rho)$ as

$$J_F(\rho) = \left|\left|\left(1 - \frac{T_d}{T(\rho)}\right) y_{\text{ini}}\right|\right|^2_{(N,\Delta)}. \tag{3}$$

From (3), we see that the minimization of $J_F(\rho)$ in (9) leads to the minimization of the relative error between the desired reference model and the actual closed loop with the obtained parameter ρ. We can easily find out in this process that the parameter $\tilde{\rho}$ is obtained just by the initial data, u_{ini} and y_{ini}. This is an brief explanation on how FRIT can achieve the desired output in the linear time-invariant case.

C. Hysteresis Model [8]

We give a brief review of hysteresis model proposed by Wakasa et.al [8] . In this reference, the following hysteresis model $\mathcal{H}_x$ was proposed

$$\begin{aligned} \mathcal{H}_x : h(k) &= \boldsymbol{H_x}(h(k-1), u(k)) \\ &= \frac{1 - h(k-1)}{1 + e^{(\alpha - u(k))\gamma}} + \frac{h(k-1)}{1 + e^{(\beta - u(k))\gamma}}, \end{aligned} \tag{4}$$

where $u \in \mathbb{R}$, $h \in (0, 1)$ and k are input, output and sampling number, respectively. $\boldsymbol{H_x}$ represents a hysteresis model which is determined by three parameters, α, β and γ $\in \mathbb{R}$. The parameters α and β are the threshold parameters, and the parameter γ is the parameter related to the gradient of the output with respect to the input respectively. These parameters are denoted by a parameterized vector $x = (\alpha, \beta, \gamma)^T$. There are several advantages in this model. One is that the model is rate-dependent, which means the shape of the hysteresis changes with the frequency of the input. Another is that the model uses just three parameters, so the computation time is less than HRNN model introduced in [7]. The other advantage is that the inverse of the model can be simply expressed as

$$\hat{\mathcal{H}}_x : u(k) = \hat{\boldsymbol{H}}_{\boldsymbol{x}}(h(k), h(k-1)) = -(\log\hat{\xi})/\gamma, \quad (5)$$

ξ is the positive solution of

$$a_2\xi^2 + a_1 + a_0 = 0, \quad (6)$$

where these coefficients are calculated from the following equations

$$\begin{aligned} a_2 &= e^{(\alpha+\beta)}\gamma h(k) \\ a_1 &= (e^{\alpha\gamma} + e^{\beta\gamma})h(k) - (e^{\alpha\gamma} - e^{\beta\gamma})h(k-1) - e^{\beta\gamma} \\ a_0 &= h(k) - 1. \end{aligned}$$

More detailed discussions can be found in the reference [8].

III. MAIN RESULTS

A. Basic Idea

We introduce a controller parameter tuning and identifying a mathematical model for systems with hysteresis in [8] by expanding FRIT to nonlinear systems.

A method that uses FRIT for IMC in a linear dynamical system in the linear time invariant case has already been proposed [10]. Our proposed architecture here is its extension for the system with nonlinear hysteresis property shown in the Fig. 2 where a plant and internal model controller is illustrated.

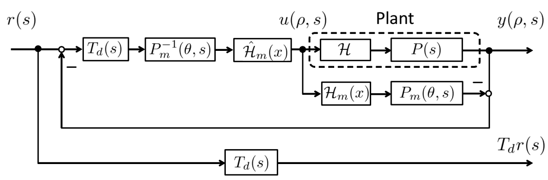

Fig. 2. IMC for system with hysteresis

We suppose that the plant consists of a static hysteresis part and a dynamic linear part. The internal model controller is given by the reference transfer function T_d, a model of the static part $\mathcal{H}_m(x)$, its inverse model $\hat{\mathcal{H}}_m(x)$, a dynamical part $P_m(\theta)$ and its inverse model $P_m^{-1}(\theta)$. $\mathcal{H}_m(x)$ and $P_m(\theta)$ depend on parameter θ and x respectively. These tuning parameters are written as $\rho = (\theta, x)$. The purpose of the system is to yield the desired output and to obtain a mathematical model of a plant,

Now we consider the fictitious reference signal for our framework. Input $u_{\text{ini}}(\rho)$ can be described as follows.

$$u_{\text{ini}} = \hat{\mathcal{H}}_m P_m^{-1} T_d (r - y_{\text{ini}} + P_m \mathcal{H}_m u_{\text{ini}}) \quad (7)$$

By solving for r in the equation, we can get the following fictitious reference signal $\tilde{r}$

$$\tilde{r} = (T_d^{-1} - 1) P_m \mathcal{H}_m u_{\text{ini}} + y_{\text{ini}}, \quad (8)$$

and the cost function can be described as

$$J_F(\rho) = ||y(\rho_{\text{ini}}) - T_d \tilde{r}(\rho)_{(N,\Delta)}||^2. \quad (9)$$

By using $\tilde{r}$, we minimize the cost function $J_F(\rho)$. Then, it is possible to obtain both a controller parameter and a model of the plant by $J_F(\rho)$.

B. Algorithm

Here we summarize the proposed method as the following steps.

1) Set the initial parameter θ_{ini} and reference model T_d.
2) Perform the initial experiment with θ_{ini} in Fig. 2. And we can obtain the initial data, u_{ini} and y_{ini}.
3) Minimize the cost function $J_F(\rho)$ in (9).
4) Implement $\tilde{\rho}$ in Fig. 2 and perform the experiment.

In the step 3), we can utilize a conventional nonlinear optimization method.

[Remark]: This paper uses CMA-ES [12] proposed in [11], for the nonlinear minimization of the cost function. This optimization does not depend on the initial parameter. This means that it is not necessary to implement the IMC architecture in Fig. 2 as the initial controller.

IV. NUMERICAL EXAMPLE

To show the validity of the proposed method, we show a numerical example. Consider

$$P = \frac{50}{0.01s^2 + s + 50}$$

as a dynamic linear part of the actual plant,

$$\begin{aligned} \mathcal{H}_x : h(k) &= \frac{1 - h(k-1)}{1 + e^{(\alpha - u(k))\gamma}} + \frac{h(k-1)}{1 + e^{(\beta - u(k))\gamma}} \\ x &= (\alpha, \beta, \gamma) \\ &= (156.3892,\ 33.5837,\ 0.1816) \end{aligned}$$

as a static hysteresis part of the plant. Of course, we assume that both of them are unknown. On the other hand, we implement the parameterized mathematical model consists of each static hysteresis part

$$\begin{aligned} \mathcal{H}_{x_m} : h(k) &= \frac{1 - h(k-1)}{1 + e^{(\alpha_m - u(k))\gamma_m}} + \frac{h(k-1)}{1 + e^{(\beta_m - u(k))\gamma_m}} \\ x_m &= (\alpha_m, \beta_m, \gamma_m) \end{aligned}$$

and a dynamical linear part

$$P_m = \frac{1}{a_m s^2 + b_m s + c_m},\ \theta = (a_m,\ b_m,\ c_m).$$

As the initial controller, we use PID controller with initial parameter $(K_P,\ K_I,\ K_D) = (500,\ 500,\ 0)$ We set the sampling period $\Delta = 0.001$ sec. By implementing the PID controller and setting sinusoidal signals as reference signal shown in Fig. 3, we obtain the initial data. The desired output y_d and the initial output y are illustrated by the chained line and the solid line respectively in Fig. 5. By using the initial data, we can solve the cost function (9).

Here, we give the reference transfer function described by $T_d = \frac{1}{0.01\times10^{-3}s^2+0.01s+1}$. Then we minimize the cost function (9) with respect to the parameter of static hysteresis part x_m and that of dynamical linear part θ_m. As a result, we obtain as

$$
\begin{aligned}
x_m &= (156.3781,\ 33.5948,\ 0.1817), \\
\theta_m &= (1.9952\times10^{-04},\ 0.02,\ 0.9994),
\end{aligned}
$$

From this, we can see the obtained model matches the actual plant appropriately. By implementing $\tilde{\rho}$ to the IMC in Fig. 2, we again perform the experiment. The input u and the output $y(\tilde{\rho})$ with the desired output y_d are illustrated in Fig. 6 and Fig. 7, respectively . We also see that the output tracks the desired output.

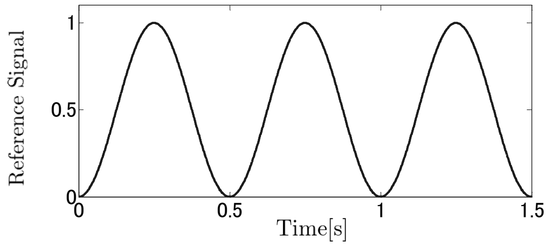

Fig. 3. The reference signal

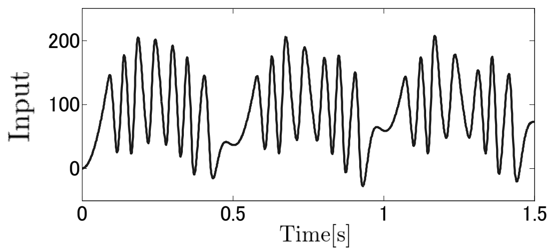

Fig. 4. The initial input

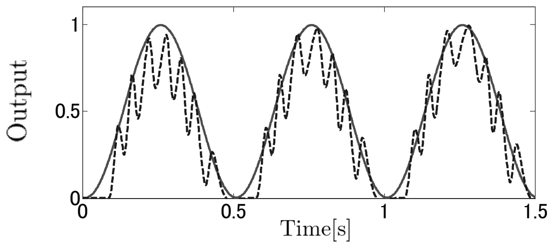

Fig. 5. The desired output y_d (the solid line), and the initial output y_{ini} (the chained line)

V. Concluding remarks

In this paper, we have proposed a data-driven tuning method of IMC for nonlinear systems with hysteresis. We have utilized FRIT to obtain the desired parameter of the IMC in which a mathematical model consisting of not only a dynamical linear part but also a static hysteresis one is implemented.

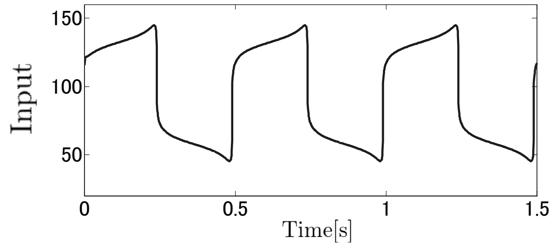

Fig. 6. The input by the tuned controller

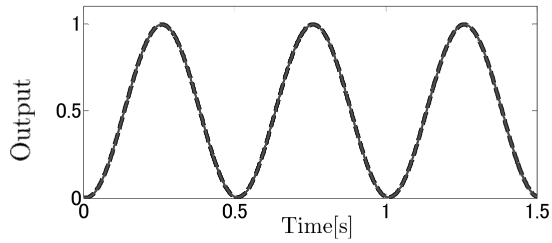

Fig. 7. The desired output y_d (the solid line), and the output y (the chained line)

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