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A novel auto-tuning PID control mechanism for nonlinear systems

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ABSTRACT

In this paper, a novel Runge–Kutta (RK) discretization-based model-predictive auto-tuning proportional-integral-derivative controller (RK-PID) is introduced for the control of continuous-time nonlinear systems. The parameters of the PID controller are tuned using RK model of the system through prediction error-square minimization where the predicted information of tracking error provides an enhanced tuning of the parameters. Based on the model-predictive control (MPC) approach, the proposed mechanism provides necessary PID parameter adaptations while generating additive correction terms to assist the initially inadequate PID controller. Efficiency of the proposed mechanism has been tested on two experimental real-time systems: an unstable single-input single-output (SISO) nonlinear magnetic-levitation system and a nonlinear multi-input multi-output (MIMO) liquid-level system. RK-PID has been compared to standard PID, standard nonlinear MPC (NMPC), RK-MPC and conventional sliding-mode control (SMC) methods in terms of control performance, robustness, computational complexity and design issue. The proposed mechanism exhibits acceptable tuning and control performance with very small steady-state tracking errors, and provides very short settling time for parameter convergence.

1. Introduction

Conventional PID controllers have been the most preferred controllers among others due to the simplicity of design and efficiency in the industrial applications and mechanical systems. The main problem about a PID controller is the fact that the parameters of the controller must be adjusted properly to satisfy a desired performance. For that purpose, many methods are proposed in the literature to tune PID parameters for linear time-invariant (LTI) systems [1–4]. Parameters of a PID controller must be tuned to provide satisfactory tracking of smooth reference signal of the linear time-varying (LTV) systems when the reference signal is variable. On the other hand, to design a PID controller for nonlinear systems, these parameters are usually tuned for local points using a linearization method. Linearization is mostly not satisfactory for all nonlinear systems due to the different linearization points and high nonlinearity. In addition, the structure of the system or reference point or environmental conditions may be changed or some internal or external disturbances may be involved in the control loop which cause different linearization points. All these circumstances lead to the necessity of one property of the PID controller: adaptation in the sense of auto-tuning. Therefore many PID controllers namely Sliding-mode (SM) adaptive PID controller for uncertain systems [5], neural-network (NN) based adaptive PID controller for the systems with unknown dynamics [6–9] and support-vector machine (SVM) based PID controller [10] have been proposed to tune PID parameters in the literature. Adaptive control scheme can be alternatively invoked a PID controller in cascade with fuzzy predictor [11]. Also, many new PID controllers which were tested for electromechanical systems are proposed in the literature [12–17].

Another popular control method namely Model Predictive Control (MPC) is used as advanced control technique in the literature. MPC-based controllers are preferred due to their advantages for linear/nonlinear system control such as handling of input and state constraints, accuracy and availability to control unstable, non-minimum phase and dead-time systems [18–21]. The design parameters, which are imposed by constraints of the system, must be large or small enough to assure nominal stability for MPC-based controllers [20]. In the constrained model-predictive control, the system must be taken away from one constraint to another. This is much more difficult for conventional structures such as PID or lead-lag compensator than MPCs. As a matter of fact, hybrid model predictive controllers have been very successful to solve such control problems. There are some studies related to hybrid MPCs. For example, to overcome stochastic disturbances and time delays, an internal model PID controller based on the Generalized Predictive Control (GPC) was developed

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in [22]. Afterwards, a different PID type controller which can be used for systems of any order based on the GPC was introduced [23]. As an other application of MPC in PID controller, the parameters of the PID are tuned with minimization of the objective function based on the CARIMA model of the systems as in [24,25]. Zhang et al. [26] proposed a novel PID controller optimized by extended non-minimal state space model predictive control framework for the temperature regulation. In [26], the proposed controller has combined the simple structure of the PID and good control performance of the MPC. In [27] Keyser et al. proposed a nonlinear extended prediction self-adaptive control (NEPSAC) mechanism which has used the nonlinear model for prediction. Other predictive control methods such as fuzzy predictive model with MPC have also been developed [28]. In the fuzzy predictive model, fuzzy control is used for controlling the uncertainty of the linear/nonlinear systems whose dynamics are unknown. In [29], a RK model-based predictive control, state and parameter estimation approach has been proposed, which inspired us to develop a robust, adaptive and predictive PID auto-tuning mechanism.

In this paper, a novel auto-tuning PID mechanism within the RK-MPC framework has been proposed for nonlinear systems. The mechanism provides some superior features in terms of control performance, robustness and design issues. In general, the proposed PID auto-tuning method includes three important characteristics: (i) robustness from the PID control structure, (ii) fast convergence from the MPC framework, (iii) adaptive behavior due to gradient-based adaptation, which constitute the main motivation of the paper. In addition to the introduction of a novel method, we have conducted two real-time control experiments on a SISO (unstable nonlinear MagLev system) and a MIMO (nonlinear three-tank liquid-level system) system. Moreover, the experimental studies include noisy and disturbance cases, and comparisons to control methods namely, standard PID, standard NMPC, RK-MPC [29] and standard SMC from the literature, which reinforces the contribution of the paper to the control theory literature.

The paper is organized as follows: Problem definition is explained in Section 2. Section 3 presents the proposed Runge–Kutta model-based PID controller structure. The real-time experimental results are shown in Section 4. The concluding remarks about the designed controller are presented in Section 5.

2. Problem statement

A nonlinear dynamical system is often expressed as the state and measurement equations. Consider an N-dimensional nonlinear continuous-time MIMO system:

$$\begin{aligned}&\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}), \quad \mathbf{y} = \mathbf{g}(\mathbf{x}, \mathbf{u}),\\ &\mathbf{u} \in \mathbf{U}, \quad \mathbf{x} \in \boldsymbol{X}, \quad \forall t \geq 0.\end{aligned} \tag{1}$$

where $\mathbf{x}(t) \in \Re^N$ is the state vector, $\mathbf{u}(t) \in \Re^R$ is the vector of control inputs and $\mathbf{y}(t) \in \Re^Q$ is the vector of output measurements. The state equations of the system are subject to state, input, input-slew and output constraints written as

$$\begin{aligned}&X_i = \{x_i \in \Re \mid x_{i_{min}} \leq x_i \leq x_{i_{max}}, i = 1, \ldots, N\}\\ &U_r = \{u_r \in \Re \mid u_{r_{min}} \leq u_r \leq u_{r_{max}}, r = 1, \ldots, R\}\\ &\Delta U_r = \{\Delta u_r \in \Re \mid |\Delta u_r| \leq \Delta u_{r_{max}}, r = 1, \ldots, R\}\\ &Y_q = \{y_q \in \Re \mid y_{q_{min}} \leq y_q \leq y_{q_{max}}, q = 1, \ldots, Q\}.\end{aligned} \tag{2}$$

In order to use proposed RK-PID mechanism for the system, it is assumed that the functions $\mathbf{f}_i(.)$ $(i = 1, \ldots, N)$ and $\mathbf{g}_j(.)$ $(j = 1, \ldots, Q)$ are known and continuously differentiable with respect to the control inputs and the state variables. Also, it is assumed that the system is controllable. In this work, a novel RK model-based auto-tuning PID controller for nonlinear continuous-time system is presented. In this structure, a discretized model of the nonlinear system which is called the RK model [29] is obtained by the fourth-order RK algorithm and then utilized for the control of the systems. The RK model of the system is used for many purposes such as control, prediction, Jacobian calculation, parameter and state estimation [29,30]. The motivation behind the use of the fourth-order RK algorithm among others is the fact that it has been proved to be very accurate and stable [31,32].

2.1. Runge–Kutta discretization method

In this study, the well-known RK integration algorithm is adopted for obtaining the discretized models of the systems under investigation due to its higher accuracy and stability properties compared to other integration methods. For a given N-dimensional nonlinear continuous-time MIMO system as in (1), the current states $(x_1[n], \ldots, x_N[n])$ and the current inputs $(u_1[n], \ldots, u_R[n])$ of the system are given at the time index n where n denotes the sampling instant at $t = nT_s$. Now, the state vector and the output measurements of the system which belong to the next sampling time can be predicted by the fourth-order RK algorithm as follows: (initially, it is set $\hat{x}_1[n] = x_1(n), \ldots, \hat{x}_N[n] = x_N[n]$)

$$\begin{aligned}&\hat{x}_1[n+1] = \hat{x}_1[n] + \tfrac{1}{6}(k_{11} + 2k_{12} + 2k_{13} + k_{14}),\\ &\vdots\\ &\hat{x}_N[n+1] = \hat{x}_N[n] + \tfrac{1}{6}(k_{N1} + 2k_{N2} + 2k_{N3} + k_{N4}),\\ &\hat{y}_1[n+1] = g_1(\hat{x}_1[n+1], \ldots, \hat{x}_N[n+1], u_1[n], \ldots, u_R[n])\\ &\vdots\\ &\hat{y}_Q[n+1] = g_Q(\hat{x}_1[n+1], \ldots, \hat{x}_N[n+1], u_1[n], \ldots, u_R[n])\end{aligned} \tag{3}$$

where

$$\begin{aligned}&k_{11} = T_s f_1(\hat{x}_1[n], \ldots, \hat{x}_N[n], u_1[n], \ldots, u_R[n]),\\ &\vdots\\ &k_{N1} = T_s f_N(\hat{x}_1[n], \ldots, \hat{x}_N[n], u_1[n], \ldots, u_R[n]),\\ &k_{12} = T_s f_1(\hat{x}_1[n] + 0.5k_{11}, \ldots, \hat{x}_N[n] + 0.5k_{N1}, u_1[n], \ldots, u_R[n]),\\ &\vdots\\ &k_{N2} = T_s f_N(\hat{x}_1[n] + 0.5k_{11}, \ldots, \hat{x}_N[n] + 0.5k_{N1}, u_1[n], \ldots, u_R[n]),\\ &k_{13} = T_s f_1(\hat{x}_1[n] + 0.5k_{12}, \ldots, \hat{x}_N[n] + 0.5k_{N2}, u_1[n], \ldots, u_R[n]),\\ &\vdots\\ &k_{N3} = T_s f_N(\hat{x}_1[n] + 0.5k_{12}, \ldots, \hat{x}_N[n] + 0.5k_{N2}, u_1[n], \ldots, u_R[n]),\\ &k_{14} = T_s f_1(\hat{x}_1[n] + k_{13}, \ldots, \hat{x}_N[n] + k_{N3}, u_1[n], \ldots, u_R[n]),\\ &\vdots\\ &k_{N4} = T_s f_N(\hat{x}_1[n] + k_{13}, \ldots, \hat{x}_N[n] + k_{N3}, u_1[n], \ldots, u_R[n]).\end{aligned} \tag{4}$$

Eq. (3) can be organized as

$$\begin{aligned}&\hat{\mathbf{x}}[n+1] = \hat{\mathbf{f}}(\hat{\mathbf{x}}[n], \mathbf{u}[n]) = \hat{\mathbf{x}}[n+1] + \mathbf{k}[n],\\ &\hat{\mathbf{y}}[n+1] = \mathbf{g}(\hat{\mathbf{x}}[n], \mathbf{u}[n]).\end{aligned} \tag{5}$$

where

$$\mathbf{k}[n] = \frac{1}{6}\begin{bmatrix} k_{11} + 2k_{12} + 2k_{13} + k_{14} \\ k_{21} + 2k_{22} + 2k_{23} + k_{24} \\ \vdots \\ k_{N1} + 2k_{N2} + 2k_{N3} + k_{N4} \end{bmatrix} = \frac{1}{6}(\mathbf{k}_1 + 2\mathbf{k}_2 + 2\mathbf{k}_3 + \mathbf{k}_4) \tag{6}$$

Now, Eq. (5) associated with the discrete-time RK-model of a continuous-time system is available for RK model-based PID controller as explained in the next section in detail.

3. The proposed Runge–Kutta model-based PID controller

Although the structure proposed in this study aims at designing PID controllers for nonlinear systems, it should be kept in mind that the designed PID controllers can work within only linear