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Practice Article

Stable adaptive PI control for permanent magnet synchronous motor drive based on improved JITL technique

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ABSTRACT

In this paper, a stable adaptive PI control strategy based on the improved just-in-time learning (IJITL) technique is proposed for permanent magnet synchronous motor (PMSM) drive. Firstly, the traditional JITL technique is improved. The new IJITL technique has less computational burden and is more suitable for online identification of the PMSM drive system which is highly real-time compared to traditional JITL. In this way, the PMSM drive system is identified by IJITL technique, which provides information to an adaptive PI controller. Secondly, the adaptive PI controller is designed in discrete time domain which is composed of a PI controller and a supervisory controller. The PI controller is capable of automatically online tuning the control gains based on the gradient descent method and the supervisory controller is developed to eliminate the effect of the approximation error introduced by the PI controller upon the system stability in the Lyapunov sense. Finally, experimental results on the PMSM drive system show accurate identification and favorable tracking performance.

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1. Introduction

Permanent magnet synchronous motor (PMSM) has received widespread acceptance in industrial servo applications of accurate speed control, because of some of its outstanding features such as superpower density, high torque to current ratio, fast response and better accuracy [1–4]. In such applications, the motion controller of PMSM may need to respond relatively swiftly to command changes and to offer enough robustness against the uncertainties of the servo system. However, the control performance of PMSM drive is still affected by uncertainties, which may come internally or externally, e.g., unpredictable plant parameter variations, external load disturbances, and unmodeled and nonlinear dynamics of the plant. Therefore, in order to enhance the performance of the PMSM drive system, control of the drive system has been a much researched topic that is still ongoing [5–8].

Recently many efforts have been made toward various modern control strategies. Roughly speaking, there are two groups of thoughts on them: model-independent strategies and model-based strategies. The model-independent control strategies have the advantage that the control process does not utilize the system identification method [9–13] but there are some other drawbacks in them. For example, in Ref. [10], an adaptive robust precision motion control scheme is developed for linear motors. However, the adaptive robust control algorithm may have several potential implementation problems. Neural network control [9] and adaptive neural dynamic surface control [12] are developed for nonlinear systems with unknown time-varying delays and a dead-zone input. One of the salient features of these control schemes is that the conventional dead-zone inverse model compensation is not needed to avoid the dead-zone identification. Meanwhile, a novel high-order neural network is proposed to approximate unknown nonlinearities. Faa-Jeng Lin et al. [11] proposed a field-programmable gate array (FPGA)-based intelligent-complementary sliding-mode control strategy. A radial-basis function-network (RBFN) estimator is employed to estimate the lumped uncertainty directly. Yet, the learning cost of the neural networks in Refs. [9,10,12] may be large, which may cause computational efficiency problems.

Model-based control strategies mainly adopt the system identification methods to obtain the model parameters which are utilized to self-tune the control parameters to optimize the control effort. In some of these control strategies, because of introducing the system identification methods and adaptation algorithms for tuning the control parameters, they simplified the structure of the controllers [15,16]. Meanwhile, in the servo drive system, the proportional–integral (PI) controller has been widely used due to its

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simple structure, robustness in operation, and easy comprehension of its principle [17]. Nevertheless, it is difficult for the traditional PI controller with fixed control parameters (i.e. proportional and integral gains) to deal with the uncertainties of the servo drive system. Thus, a variety of model-based control strategies for adaptive PI controllers (i.e. PI self-tuning strategies) have been proposed in recent years [18,19].

For the simplicity and feasibility of adaptive PID controllers, model-based self-tuning strategies appear to be more suitable for real-time system. Some of these tuning strategies have been designed by incorporating empirical models like neural networks [20,21], fuzzy neural networks models [22–25] and local model networks [14]. However, the problem of how to partition the operating regimes remained an ad-hoc procedure and therefore a prior knowledge of the processes, which might not be readily accessible in most practical cases, might be needed for determining the structure of the networks [14]. Instead of incorporating empirical models, some other popular PI tuning strategies have applied the dynamic linear model to approximate the nonlinear characteristics in the control process [15,16,26,27]. The dynamic linear model identification methods have been introduced as an effective solution to the nonlinear systems identification problem [14,15]. Xu [26] presented a novel supervised receding horizon optimal scheme to self-tune PI parameters. Due to the abandonment of the past data, the identified model might not be accurate enough. Another technique was utilizing the recursive least squares (RLS) algorithm to identify the local model [15]. Yet poor estimation of system parameters would occur if the online process input and output data did not meet excitation conditions [14]. Similar approaches for self-tuning PID controllers were also investigated based on the just-in-time learning (JITL) technique [27–31]. In these works, basically, the parameters of the process model are updated according to different identification methods and then based on the identified model the PID parameters are calculated by the corresponding adaptation algorithm.

For various PID tuning strategies, the stability of the controlled system should be adequately considered. In Refs. [32–34], a supervisory controller was introduced to guarantee the stability of the closed-loop PID control system. However, only continuous-time dynamic system was considered. Yet, most of the practical digital systems such as the PMSM drive system are implemented in discrete-time domain. Therefore, to implement the adaptive PI controller on the PMSM drive system and other similar practical digital systems the PI tuning strategy should be researched in the discrete-time domain.

Motivated by the previous works, a stable adaptive PI control strategy based on improved JITL (IJITL) technique is proposed for the PMSM drive system in this paper. In the proposed method, the model parameters of the servo system are obtained by IJITL, which is one of the dynamic linear model identification methods. The conventional JITL is investigated not only because of its prediction capability for nonlinear systems but also its inherent adaptive nature. The latter feature enables the JITL to use process data collected around the nominal operating condition to build the database for modeling purpose. Nevertheless, the initial database of the conventional JITL should include all kinds of operating conditions, which makes the initial database considerably huge. Furthermore, the size of the database will increase continuously when adopting the traditional database updating strategy. Therefore, the time spent on collecting data samples in the database will become considerably long. Thus it cannot meet the high real-time requirement of the PMSM drive system [35]. IJITL increases the computational efficiency significantly by improving the database updating strategy and the method to calculate the model parameters. With higher efficiency, IJITL is more suitable for the online identification of the PMSM drive system. Despite the expense of the identification accuracy of conventional JITL, IJITL is still superior to its conventional counterparts such as RLS. Moreover, to the best of the authors' knowledge, traditional JITL is only conducted in simulation test and has not been applied in practical systems for its heavy computational burden. At each sampling instance, the current identified local model is incorporated in the adaptive PI controller design to determine the optimal control effort. The proposed adaptive PI controller is designed in the discrete-time domain and is composed of a PI controller and a supervisory controller. The PI gains can automatically be tuned online based on the gradient descent method to minimize the tracking error. By introducing a supervisory controller, the stability of the PMSM servo system with the plant uncertainty and external disturbance can be guaranteed in the Lyapunov sense. The proposed adaptive PI controller is then applied to a PMSM drive. In addition, the proposed adaptive controller is not designed for a special PMSM drive system and hence it can be used for any PMSM drive. Furthermore, the approach can be used to identify and control other electrical or mechanical systems which have high real time requirement.

This paper is organized as follows. In Section 2, the mathematical model of the PMSM drive system is described. The IJITL identification method is presented in Section 3. In Section 4, the design detail of the stable adaptive PI controller is derived in the discrete-time domain and the overall adaptive control scheme is given. The convergence analysis of the proposed adaptive controller is also given in this section. Finally in Section 5, experimental results are presented to illustrate the proposed control strategy and its conventional counterparts for comparison.

2. Mathematical model of the PMSM drive system

The general structure of the PMSM servo system is shown in Fig. 1. The overall system mainly contains a PMSM, a field-orientation mechanism, a space vector pulse width modulation (SVPWM), a voltage-source inverter, and three controllers. The controllers apply a structure of cascade control loops consisting of a speed loop and two current loops. As is shown in Fig. 1, the d axis component of the stator current vector is forced to be zero to make the electromagnetic torque directly proportional to the q axis component. In the high-performance speed control for PMSM drive system, compared with speed loop, the current loops have considerably wide bandwidths, which ensure a great tracking performance. As a result, the transfer function of the current loops is usually regarded as unity. Therefore, the task here is to design an adaptive PI controller for the speed loop.

Based on the above analysis, the average model of speed control for PMSM drive system is shown in Fig. 2. Accordingly, the mathematical model can be reasonably expressed in Laplace domain as

$$\omega(s) = \frac{K_t {i_q}^*(s) - T_L(s)}{Js + B} \tag{1}$$

where ω is the shaft speed; ${i_q}^*$ is the q axis command current component; K_t is the torque coefficient; T_L is the disturbance torque; B is the viscous damping coefficient; and J is the inertia coefficient of the rotating masses.

The disturbance torque can be given as

$$T_L = T_{load} + T_f + T_{cog} + T_n \tag{2}$$

where T_{load} is the load torque; T_f is the friction torque mainly depending on the speed of the motor; T_{cog} is the cogging torque produced by the magnetic attraction between the rotor mounted permanent magnets and the stator [2]; and T_n is the torque caused by other uncertainties. The main disturbance torque is load torque

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