High-Order Terminal Sliding-Mode Observer for Parameter Estimation of a Permanent-Magnet Synchronous Motor

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***Abstract*—This paper proposes a terminal sliding-mode (TSM) observer for estimating the immeasurable mechanical parameters of permanent-magnet synchronous motors (PMSMs) used for complex mechanical systems. The observer can track the system states in finite time with high steady-state precision. A TSM control strategy is designed to guarantee the global finite-time stability of the observer and, meanwhile, to estimate the mechanical parameters of the PMSM. A novel second-order sliding-mode algorithm is designed to soften the switching control signal of the observer. The effect of the equivalent low-pass filter can be properly controlled in the algorithm based on requirements. The smooth signal of the TSM observer is directly used for the parameter estimation. The experimental results in a practical CNC machine tool are provided to demonstrate the effectiveness of the proposed method.**

***Index Terms*—Observers, parameter estimation, permanent-magnet motors, sliding-mode control (SMC).**

I. Introduction

THE CURRENT focus of advanced manufacturing technology is on high precision, high speed, high efficiency, and high reliability. As motor control systems play an important role in reaching this goal, improvement in performance and efficiency of motor control systems is needed. State and parameter estimation for motor control systems is a key factor that influences the performance of complex mechanical systems, such as industrial robots, CNC machine tools, and automated manufacturing systems. The mechanical parameters needed to be estimated in motor control systems used for mechanical systems include the moment of inertia of the motor rotor and the load, the viscous damping coefficient, and the load torque, which together determine the dynamics of the motor control systems. Once these parameters are estimated accurately, the controllers of a motor control system can be autotuned, the system can be designed using optimal control theory, and the performance of the system can be improved.

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The basic method for estimating the mechanical parameters of a motor control system is the run-out method or the coasting test, which is an experimental method. The main advantage of the method is that it can be conducted with the complete drive in place and operable, which requires no prior knowledge about details of the plant. The accuracy obtainable is adequate for most applications of motor control systems [1]. However, this method is very difficult for practical applications, as it needs a motor acceleration signal and requires the driver power to be switched off during the test. Aside from the run-out method, a number of alternative methods for parameter estimation have been proposed. These methods mainly fall into four categories: speed response-based method, extended Kalman filter (EKF) and recursive least square (RLS) estimators, model reference adaptive system (MRAS), and observer-based method.

A speed response-based method was used to estimate the mechanical parameters of a motor using its speed response. An identification method of the inertia and the viscous damping coefficient was proposed and applied to a drive system in [2]. An inertia calculation method was presented to detect the periodic inertia variation in [3]. These algorithms are simple but not robust because of the open-loop feature.

EKF and RLS estimators can be applied for parameter and state estimation [4]–[8]. Although they are recursive, it is difficult for real applications because the gain is limited and the algorithm is sensitive to mechanical noise and parameters of system.

The MRAS-based method is to estimate inertia using Landau's discrete time-recursive parameter identification [9], [10]. Its advantage is that it requires relatively simple implementation. However, the performance of the method is sensitive to parameter variations of the motor system. In addition, it cannot estimate the time-varying load torque in real time.

Observer-based methods are an important means for parameter estimation. An extended observer [11] was proposed to estimate the unknown load torque, the motor speed, and the acceleration. An estimation algorithm for identifying inertia [12] was presented by an observer. The design and implementation of the algorithms in [11] and [12] are simple, but both of them have poor robustness. In [13], an observer was designed to estimate the mechanical parameters. Its structure is very simple, but it can only estimate slow varying load torque. Sliding-mode control (SMC) has been studied extensively and widely used in many applications [14]–[20]. Meanwhile, sliding-mode observers can be applied toward the parameter estimation because of their computational simplicity, high robustness to the disturbances, and low sensitivity to the system parameter variations. A number of observer-based state and parameter estimation schemes have been proposed. In [21], a sliding-mode observer based on the LuGre friction model was proposed to estimate the friction. Unfortunately, it needs a low-pass filter to extract the estimated signal, which will incur the phase lag and affect the estimation accuracy and speed. Recently, the second-order sliding-mode observer has been applied to the observation and identification of mechanical systems [22], [23]. However, the perturbation identification still needs a low-pass filter.

The aforementioned observers are based on the conventional sliding-modes, i.e., linear sliding-modes (LSMs) [24], [25]. Conventional SMC systems adopt LSM controllers. In order to obtain faster and finite-time convergence, and higher steady-state precision, a terminal sliding-mode (TSM) control was developed in [26] and [27]. For overcoming the singularity in TSM systems, a global nonsingular TSM control was proposed in [28] and applied later in a permanent-magnet synchronous motor (PMSM) control system in [29].

This paper proposes a TSM observer-based method for estimating the mechanical parameters of a PSMS control system used in complex mechanical systems. A TSM observer is designed to track the system states within finite time and, meanwhile, to estimate the mechanical parameters of the PMSM control system. A novel second-order sliding-mode algorithm is designed to be equivalent to a low-pass filter, which can soften the switching control signal of the TSM observer. The effect of the filter can be properly controlled by regulating the parameters in the algorithm. The smooth control signal of the observer is directly used for the parameter estimation in real time, and no phase lag of the estimation incurs. Some experiments are carried out in a CNC machine tool, and the parameter estimation results are analyzed and compared with available practical data to validate the proposed method.

This paper is organized as follows. Section II introduces the problem statement which is a PMSM expressed by both an electrical and a mechanical model. In Section III, a TSM observer is presented, and its design method is described. Section IV presents a parameter estimation method of a PMSM control system using the proposed TSM observer. In Section V, the experimental results are presented and analyzed extensively. Finally, conclusions are drawn in Section VI.

II. Problem Statement

The motor under investigation is a PMSM, which has been widely used in many applications, such as CNC machine tools, process control systems, industrial robots, home appliances, computer peripherals, medical instruments, and aerospace. This is because of its advantageous features, including simple structure, high efficiency, high power density, high torque-to-inertia ratio, low maintenance cost, and robustness.

A typical PMSM control system, as shown in Fig. 1 [30], generally consists of three feedback control loops: the current, speed, and position loops. The design task of the PMSM control systems is to design the three controllers: the position, speed,

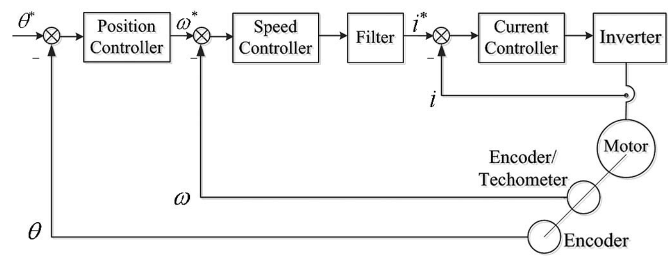

Fig. 1. Typical control system of PMSM.

and current controllers. In addition, a filter is involved in the speed loop. It is generally a notch filter that passes all frequencies except those in a stopband centered on a center frequency for suppressing the low-frequency mechanical resonance in the motor control systems.

The design of the current controller is relatively easy because its parameters mainly depend on the resistances and the inductances of the stator, both of which are time invariant and can be measured. The design of the position controller is predominantly based on the parameters estimated for the speed loop and is also relatively easy. Thus, the speed controller is the key to achieving the performance objectives of the motor control system, such as depressing the effect of the mechanical resonance, backlash, and friction.

Assume that the magnetic flux of the motor is not saturated, the magnetic field is sinusoidal, and the influence of the magnetic hysteresis is negligible. The dynamics of a PMSM can be described by both an electrical model in the $d-q$-axes [30]

$$\begin{cases} \dot{i}_d = -R_s i_d/L + p\omega i_q + u_d/L \\ \dot{i}_q = -p\omega i_d - R_s i_q/L - p\psi_f\omega/L + u_q/L \end{cases} \tag{1}$$

and a mechanical model [30]

$$\begin{cases} \dot{\theta} = \omega \\ J\dot{\omega} + B\omega + T_L = T_M \end{cases} \tag{2}$$

where u_d and u_q are the $d-q$-axis stator voltages, i_d and i_q are the $d-q$-axis stator currents, L is the $d-q$-axis inductance, R_s is the stator winding resistance, ψ_f is the rotor flux, p is the number of pole pairs, T_M is the driving torque $(N \cdot m)$, T_L is the load torque $(N \cdot m)$, J is the moment of inertia of the motor rotor and the load $(\mathrm{kg \cdot m^2})$, B is the viscous damping coefficient, ω is the angular speed of the motor (rad/s), and θ is the angular position of the motor (rad).

The driving torque in (2) can be expressed as follows [12]:

$$T_M = \left(\frac{3p}{2}\right)(\psi_f i_q + (L_d - L_q)i_d i_q) \tag{3}$$

where L_d and L_q denote the d- and q-axis inductances.

Based on the principle of the vector control, the d-axis current i_d in (1) and (3) should be controlled to be zero in the current loop. Therefore, (3) can be rewritten as

$$T_M = \left(\frac{3p}{2}\right)\psi_f i_q = K_q i_q \tag{4}$$

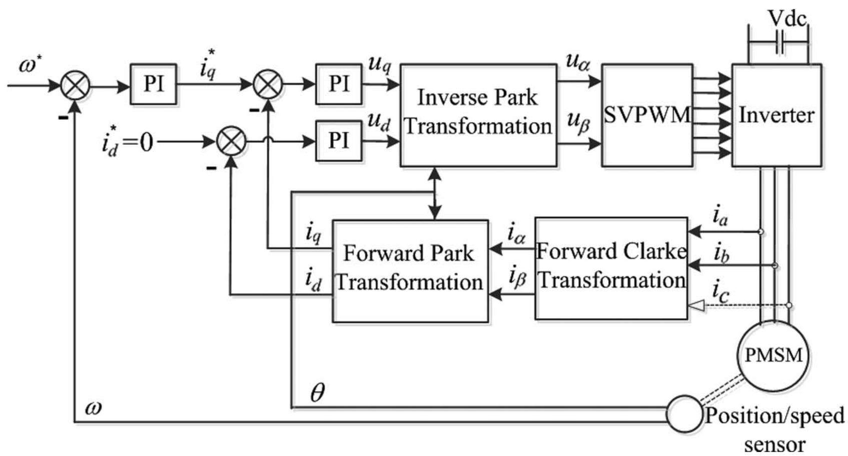

Fig. 2. PMSM vector control system based on PI controllers.

where $K_q = (3p/2)\psi_f$ denotes an electrical–mechanical energy conversion constant, or simply a torque constant. T_M is only proportional to i_q, and K_q is a constant, which means that T_M can be controlled only by the q-axis current i_q.

In practical applications, the stator currents can be directly measured using the current sensors (resistor or Hall-effect sensor), as shown in Fig. 2. i_d and i_q can then be obtained using the Park–Clarke transformation. After obtaining i_q, T_M can be calculated using (3) or (4). It should be noticed that the load torque T_L in (2) is not directly available for measurement, so T_L should be treated as a disturbance. It includes all nonlinearities of the system, the load torque, as well as the disturbance.

The dynamics of a PMSM can be expressed by both the electrical and mechanical models. The former can be used to design the two current controllers, while the latter can be used to design the speed controller, as shown in Figs. 1 and 2.

The parameters in the dynamics of a PMSM can be divided into two groups: electrical and mechanical parameters. The electrical parameters include L, R_s, L_d, L_q, ψ_f, p, and K_q in (1) and (3), while the mechanical parameters include J, B, and T_L in (2). The electrical parameters are mainly used for the design of the current controllers. They are all constants and can be measured using instruments or sensors. This paper focuses on the estimation of the mechanical parameters J, B, and T_L. They are immeasurable and play an important role in designing the speed controller, which will determine both the dynamical and steady-state performances of a PMSM control system.

The design of the speed controller in Figs. 1 and 2 is mainly based on the mechanical model of a PMSM (2). In order to achieve good performances of a PMSM control system, the mechanical parameters J, B, and T_L in (2) should be estimated with good accuracy. It should be noted that both J and B are generally time invariant for the same operation condition of a PMSM control system, but T_L is always time varying. Here, the objective of the parameter estimation is to estimate J, B, and T_L using the practical online measurements, T_M, ω, and θ, where T_M is obtained by measuring the stator currents, calculating the Park–Clarke transformation, and plugging i_q in (4). The purpose of the parameter estimation is to design the optimal motor speed controller and to autotune the motor speed controller.

III. TSM Observer Design

For the purpose of parameter estimation, considering the mechanical dynamic model of the PMSM (2), a sliding-mode observer can be designed as follows:

$$\begin{cases} \dot{\hat{\theta}} = \hat{\omega} \\ \hat{J}_0\dot{\hat{\omega}} = -\hat{B}_0\hat{\omega} + T_M + u \end{cases} \tag{5}$$

where $\hat{\theta}(t)$ and $\hat{\omega}(t)$ represent the state estimation for $\theta(t)$ and $\omega(t)$, respectively; T_M is the driving torque, the same as that of (2); $u \in R$ is the error compensation signal of the TSM observer that will take the feedback into the design of the observer; and $\hat{J}_0 \in R$ and $\hat{B}_0 \in R$ are two nominal parameters that are some crude estimations of the true parameters in (2), i.e.,

$$J = \hat{J}_0 + \Delta\hat{J}_0; \quad B = \hat{B}_0 + \Delta\hat{B}_0 \tag{6}$$

where $\Delta\hat{J}_0$ and $\Delta\hat{B}_0$ are two errors between the true system parameters and their crude estimations, respectively. $\hat{J}_0$ and $\hat{B}_0$ can be determined initially based on the experiences and prior knowledge. It should be noticed that accuracy is not necessary for either parameters.

Although the exact values of the three system parameters and their estimations are unknown, one can reasonably assume that $\Delta\hat{J}_0$, $\Delta\hat{B}_0$, and T_L are bounded by the quantities in the following form:

$$\begin{aligned} |\Delta J_0| &= |J - \hat{J}_0| \le K_J \\ |\Delta B_0| &= |B - \hat{B}_0| \le K_B \\ |T_L| &\le K_L; \quad |\dot{T}_L| \le K_{dL} \end{aligned} \tag{7}$$

where K_J, K_B, K_L, and K_{dL} are all positive constants.

For the mechanical dynamic model of a PMSM (2), except for the time-varying load torque $T_L(t)$, both J and B are constants. Before conducting parameter estimation, the boundaries of the unknown parameters $T_L(t)$, J, and B can always be assumed as in (7). These boundaries can be used for designing the observer.

In fact, it is not necessary to estimate the motor position or speed using (5). Both of them can be directly measured using an optical encoder, or a resolver. The purpose of the observer (5) is for the estimation of the parameters J, B, and T_L.

From (2) and (5), the error system can be obtained as

$$J\dot{\omega} - \hat{J}_0\dot{\hat{\omega}} = -B\omega - T_L + \hat{B}_0\hat{\omega} - u. \tag{8}$$

Define $e_1 = \theta - \hat{\theta}$ and $e_2 = \omega - \hat{\omega}$. Then, (8) can be rewritten as

$$\begin{cases} \dot{e}_1 = e_2 \\ \hat{J}_0\dot{e}_2 = -\Delta J_0\dot{\omega} - B\omega - T_L + \hat{B}_0\hat{\omega} - u \end{cases} \tag{9}$$

or

$$\begin{cases} \dot{e}_1 = e_2 \\ \dot{e}_2 = -\Delta J_0\dot{\omega}/\hat{J}_0 - \Delta B_0\omega/\hat{J}_0 - T_L/\hat{J}_0 \\ \qquad -B_0(\omega - \hat{\omega})/\hat{J}_0 - u/\hat{J}_0. \end{cases} \tag{10}$$

The error compensation signal u is chosen as

$$u = u_1 + u_2 \tag{11}$$

$$u_1 = -\hat{B}_0(\omega - \hat{\omega}) = -\hat{B}_0 e_2 \tag{12}$$

where u_1 is directly related to the speed estimation error between the measurement of the motor speed and its estimation; u_2 is another control signal whose design will be described later. Using (11), (10) can be rewritten in the following form:

$$\begin{cases} \dot{e}_1 = e_2 \\ \dot{e}_2 = -\Delta J\dot{\omega}/\hat{J}_0 - \Delta B_0\omega/\hat{J}_0 - T_L/\hat{J}_0 - u_2/\hat{J}_0. \end{cases} \tag{13}$$

Assumption 1: The motor acceleration and jerk are bounded

$$|\dot{\omega}(t)| \le a_m, |\ddot{\omega}(t)| \le j_m \tag{14}$$

where $a_m = \max(|\dot{\omega}(t)|)$ and $j_m = \max(|\ddot{\omega}(t)|)$ are two constants.

Assumption 2: $u_2(t)$ in (13) satisfies the following condition:

$$T\,|u_2(t)| \le K_{Tu} \tag{15}$$

where T and K_{Tu} are also two positive constants.

Since $u_2(t)$ in (13) cannot be infinite and is always limited to a possible value, the assumption (15) is reasonable.

Theorem 1: The observer error e_2 and its derivative in (13) will converge to zero in finite time if a TSM manifold is chosen as (16) and the control signal u_2 is designed as (17)

$$s = e_2 + \beta\dot{e}_2^{p/q} \tag{16}$$

$$\dot{u}_2 + Tu_2 = v \tag{17a}$$

$$v = \left(\frac{\hat{J}_0 q}{\beta p}\right)\dot{e}_2^{2-p/q} + (K_J j_m + K_B a_m + K_{dL} + K_{Tu} + \eta)\mathrm{sgn}(s) \tag{17b}$$

where p and q are all odd numbers and $1 < p/q < 2$, $\eta > 0$. K_J, K_B, and K_{dL} are defined in (7), j_m and a_m in (14), and T and K_{Tu} in (15).

Proof: The following Lyapunov function is considered: $V = 0.5s^2$. Differentiating V with respect to time t gives

$$\dot{V} = s\cdot\dot{s} = \left(\frac{\beta p}{q}\right)\dot{e}_2^{p/q-1}\left(\left(\frac{q}{\beta p}\right)\dot{e}_2^{2-p/q} + \ddot{e}_2\right)s. \tag{18}$$

From (10), (18) can be rewritten as

$$\dot{V} = \left(\frac{\beta p}{\hat{J}_0 q}\right)\dot{e}_2^{p/q-1}\left(\left(\frac{\hat{J}_0 q}{\beta p}\right)\dot{e}_2^{2-p/q} - \Delta J\ddot{\omega} - \Delta B_0\dot{\omega} - \dot{T}_L - \dot{u}_2\right)s. \tag{19}$$

Substituting (17) into (19) gives

$$\begin{aligned}\dot{V} &= \left(\frac{\beta p}{\hat{J}_0 q}\right)\dot{e}_2^{p/q-1} \times \left(\left(\frac{\hat{J}_0 q}{\beta p}\right)\dot{e}_2^{2-p/q} - \Delta J\ddot{\omega} - \Delta B_0\dot{\omega} - \dot{T}_L - v + Tu_2\right)s \\ &= \left(\frac{\beta p}{\hat{J}_0 q}\right)\dot{e}_2^{p/q-1} \times \Big(-\Delta J\ddot{\omega} - \Delta B_0\dot{\omega} - \dot{T}_L + Tu_2 \\ &\qquad - (K_J j_m + K_B a_m + K_{dL} + K_{Tu} + \eta)\mathrm{sgn}(s)\Big)s.\end{aligned}$$

That is

$$\dot{V} \le -\left(\frac{\beta p}{\hat{J}_0 q}\right)\dot{e}_2^{p/q-1}\eta|s|. \tag{20}$$

Since p and q are odd numbers and $1 < p/q < 2$, the term $\dot{e}_2^{p/q-1}$ has two possible cases: $\dot{e}_2^{p/q-1} > 0$ for $\dot{e}_2 \ne 0$ and $\dot{e}_2^{p/q-1} = 0$ only for $\dot{e}_2 = 0$. Meanwhile, for $|s| \ne 0$, there are also two different cases: 1) $\dot{e}_2 \ne 0$, and 2) $\dot{e}_2 = 0$ but $e_2 \ne 0$. For the former case, i.e., $|s| \ne 0$ and $\dot{e}_2 \ne 0$, it can be obtained from (20) as follows:

$$\dot{V} \le -\left(\frac{\beta p}{\hat{J}_0 q}\right)\dot{e}_2^{p/q-1}\eta|s| < 0 \quad \text{for} \quad |s| \ne 0.$$

For the latter case, $|s| \ne 0$, $\dot{e}_2 = 0$ but $e_2 \ne 0$, the system states will not always stay on the point ($\dot{e}_2 = 0$, $e_2 \ne 0$) and will continue to cross the axis $\dot{e}_2 = 0$ in the phase plane $0 - e_2\dot{e}_2$ [28].

Therefore, from the aforementioned proof, the system states can reach $s = 0$ within finite time. Suppose that t_r is the time when s reaches zero from $s(0) \ne 0$, i.e., $s(t) = 0$, $\forall t \ge t_r$. From $s = e_2 + \beta\dot{e}_2^{p/q} = 0$, the solution for $e_2(t)$ and t_r can be expressed as follows:

$$e_2(t) = \begin{cases} \left(e_2^{1-q/p}(0) - (1-q/p)\beta^{-q/p}t\right)^{p/(p-q)} \\ \quad \times\, \mathrm{sgn}e_2(0), \qquad t < t_s \\ 0, \qquad t \ge t_s \end{cases} \tag{21}$$

$$t_s = \frac{p\beta^{q/p}}{p-q}e_2^{1-q/p}(0). \tag{22}$$

It can be seen that $e_2(t)$ and its derivative in (13) can converge to zero along $s = 0$ in finite time t_s. This completes the proof.

For designing the parameters of the TSM manifold (16), now, the steady-state errors of a TSM system are analyzed. It is well known that, in the ideal sliding-mode, the sliding-mode manifold s is always zero. However, in reality, s cannot be guaranteed to be always zero because of the following two reasons: 1) The actuators exhibit the time delay feature, and 2) for eliminating the chattering in the SMC systems, a saturation function $\mathrm{sat}(\cdot)$ is generally used to replace the signum function $\mathrm{sgn}(\cdot)$. Assume that there exists a layer surrounding the sliding-mode manifold $s = 0$ and the width of the layer is φ, which is a constant. The existence condition of the sliding-mode is $s\dot{s} < 0$ only for $|s| \geq \varphi$, which means that the steady-state error of the sliding-mode manifold is $|s| < \varphi$. From (16), the relationship between the steady-state errors of the SMC system states and the width of the layer φ can be expressed by

$$\begin{cases} |e_1(t)| < \left(\frac{\phi}{\beta}\right)^{p/q} \\ |e_2(t)| < 2\phi \end{cases} \text{subject to } |s| < \varphi. \tag{23}$$

Remark 1: Three parameters in the TSM manifold (16), β, p, and q, can be determined based on the requirements for the response speed (22) or the steady-state tracking precision (23) of the observer error states. If β is unchanged, the bigger the value of p/q is, the faster the system states move along $s = 0$, but the larger the steady-state tracking precision. If p/q is unchanged, the bigger the β is, the slower the system states move along $s = 0$, but the smaller the steady-state tracking precision.

Remark 2: In Theorem 1, the control strategy is equivalent to a low-pass filter, where $v(t)$ is the input and $u_2(t)$ the output. The Laplace transfer function of the filter (17a) is

$$\frac{u_2(s)}{v(s)} = \frac{1}{(s+T)} \tag{24}$$

where $\omega = T$ is the bandwidth of the low-pass filter. Although the signal $v(t)$ in (17b) is nonsmooth because of the switch function, the actual control signal of the observer $u_2(t)$ is the output of the low-pass filter (24) and is softened by (17a) to be a smooth signal. From the proof of Theorem 1, it can be seen that the value of $T > 0$ in the low-pass filter (24) does not affect the stability of the observer. Therefore, T can be designed arbitrarily based on the requirement of softening $v(t)$, given that the condition of (15) is satisfied. Hence, the control signal of the observer, $u_2(t)$, cannot induce the chattering phenomenon in the system because of the low-pass filter and can be directly used for the parameter estimation.

IV. Parameter Estimation of Mechanical Dynamics

In order to estimate the mechanical parameters of a PMSM control system accurately, the system should be actuated in some special operation. The three mechanical parameters to be estimated can be divided into two groups. The first group includes two parameters: the viscous damping coefficient B and the moment of inertia J. The second group is the load torque T_L. The former two parameters are generally time invariant, while the latter is time varying.

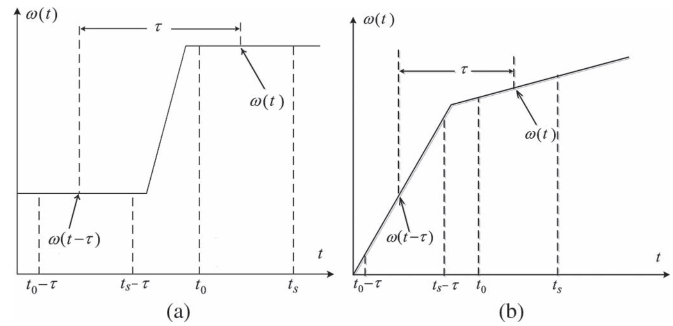

Fig. 3. Principle of parameter estimation. (a) Estimating B. (b) Estimating J.

During parameter estimation, the motor can be operated in the speed closed-loop control mode or the position closed-loop control mode. The measurements in the system for parameter estimation are the motor speed, the motor position, and the q-axis stator current.

The principle of the parameter estimation is shown in Fig. 3 and can be described as follows: 1) When estimating B, as shown in Fig. 3(a), the motor is required to operate at two different constant speeds for a period of time, and during these two periods of time, the motor speed, the motor position, and the q-axis stator current are measured and used for estimating B; and 2) when estimating J, as shown in Fig. 3(b), the motor is required to operate at two different constant accelerations or decelerations for a period of time, respectively. During these two periods of time, the motor speed, the motor position, and the q-axis stator current are also measured and used for estimating J.

For a PMSM (2), its observer (5) can be designed according to Theorem 1. The error system (13) will converge to $s = 0$ in finite time, and e_2 and its derivative in error system (13) will converge to zero along $s = 0$ in finite time. When $e_2(t) = 0$ and $\dot{e}_2(t) = 0$, from (13), it can be obtained as follows:

$$-\Delta J_0\dot{\omega}(t) - \Delta B_0\omega(t) - T_L(t) - u_2(t) = 0. \tag{25}$$

Based on (25), three mechanical parameters of a PMSM control system can be estimated using the proposed method in the following steps.

Step 1: Estimation of B

Before parameter estimation, the three mechanical parameters B, J, and T_L are unknown and cannot be used to design the motor speed controller. At this stage, a nonoptimal PI controller can be used as the speed controller, whose parameters can be tuned using a trial-and-error method. This controller may lead to poor performance of the PMSM control system. However, since the parameter estimation needs only the steady-state information of the PMSM control system, the nonoptimal controller has little effect on the parameter estimation, i.e., the TSM observer (5) and its control strategy in Theorem 1 are independent of the motor speed controller. Here, the task is to estimate the parameter B. The estimation of B is $\hat{B} = \hat{B}_0 + \Delta\hat{B}_0$. Since the crude estimation $\hat{B}_0$ is assumed to be known, the task is, in fact, to estimate the difference $\Delta\hat{B}_0$.

As shown in Fig. 3(a), delaying (25) by a constant time τ gives

$$-\Delta J_0\dot{\omega}(t-\tau)-\Delta B_0\omega(t-\tau)-T_L(t-\tau)-u_2(t-\tau)=0 \tag{26}$$

where τ is a constant time delay.

For estimating B, we can utilize two different constant motor speeds, $\omega(t)$ and $\omega(t-\tau)$, i.e., $\omega(t)\neq\omega(t-\tau)$, $\dot{\omega}(t)=0$, and $\dot{\omega}(t-\tau)=0$ for a period of time. In practical applications, such a task is not difficult because we only need to control a motor to rotate at two different constant speeds for several seconds. From the theoretical analysis and the observation of experiments, it can be assumed that the load torque $T_L(t)$ is unchanged when the motor reaches its constant steady-state speed. Therefore, the conditions for the estimation of B are as follows: 1) $T_L(t)=T_L(t-\tau)$ (assumption); 2) $\omega(t)$ and $\omega(t-\tau)$ are all constants, but $\omega(t)\neq\omega(t-\tau)$; and 3) $\dot{\omega}(t)=0$ and $\dot{\omega}(t-\tau)=0$ for $t_0<t<t_s$, where t_0 and t_s are the start and the end time for the estimation of B, respectively, and τ is a time delay, as shown in Fig. 3(b). Subtracting (26) from (25) gives

$$-\Delta B_0\left(\omega(t)-\omega(t-\tau)\right)-\left(u_2(t)-u_2(t-\tau)\right)=0 \tag{27}$$

and then

$$\Delta\hat{B}_0=-\frac{u_2(t)-u_2(t-\tau)}{\omega(t)-\omega(t-\tau)}. \tag{28}$$

From (28) and (6), the estimation of B can be obtained as

$$\hat{B}=\hat{B}_0+\Delta\hat{B}_0=\hat{B}_0-\frac{u_2(t)-u_2(t-\tau)}{\omega(t)-\omega(t-\tau)}. \tag{29}$$

The estimation algorithm (29) cannot be directly applied for traditional sliding-mode observers because of the nonsmooth $u_2(t)$. In our proposed observer, although $v(t)$ in (17) has a switch function, $u_2(t)$ in (17) and (29) is smooth and can be directly used for the estimation algorithm (29). This is one of the academic contributions in this paper.

Step 2: Estimation of J

After estimating B, we can assume $\hat{B}=B$ and $\Delta\hat{B}_0=0$ in (6) and then update the control strategy (17) as

$$\dot{u}_2+Tu_2=v \tag{30a}$$

$$v=\left(\frac{\hat{J}_0 q}{\beta p}\right)\dot{e}_2^{2-p/q}+\left(K_J j_m+K_{dL}+K_{Tu}+\eta\right)\operatorname{sgn}(s) \tag{30b}$$

and in this case, (25) can be rewritten as

$$-\Delta J_0\dot{\omega}(t)-T_L(t)-u_2(t)=0. \tag{31}$$

For estimating J, the motor is required to rotate at a constant acceleration a_2 for a period of time and then at a different constant acceleration a_1 for another period of time, as shown in Fig. 3(b). Suppose that a_1 corresponds to the control signal of the observer $u_2(t)$ and a_2 corresponds to $u_2(t-\tau)$, τ is a constant time delay, which means that two different constant accelerations correspond to two different periods of time, respectively, as shown in Fig. 3(b). Delaying (31) by τ gives

$$-\Delta J_0\dot{\omega}(t-\tau)-T_L(t-\tau)-u_2(t-\tau)=0. \tag{32}$$

Subtracting (32) from (31) gives

$$-\Delta J_0\left(\dot{\omega}(t)-\dot{\omega}(t-\tau)\right)-\left(u_2(t)-u_2(t-\tau)\right)=0 \tag{33}$$

and then

$$\Delta J_0=-\frac{u_2(t)-u_2(t-\tau)}{a_1-a_2}. \tag{34}$$

Finally, from (34), the estimation of J can be obtained as

$$\hat{J}=\hat{J}_0-\frac{u_2(t)-u_2(t-\tau)}{a_1-a_2}. \tag{35}$$

Step 3: Estimation of Time-Varying T_L

In practical applications, B is generally time invariant. J may change when the operation condition changes, for example, tool changing in CNC machine tools, but this does not happen frequently. Generally, J can be considered as time invariant for the same operation condition. Therefore, once B and J are estimated accurately, they can be regarded as constants. However, the load torque T_L may vary during the operation, for example, when a cutting tool or an end mill of a CNC machine tool cuts a thin or thick workpiece or tracks some different trajectories, T_L may always change. In addition, although the mechanical dynamics of a PMSM system can be expressed by a linear equation (2), a practical PMSM system is, in fact, nonlinear, and the linear model (2) is only its approximation. We can consider all possible nonlinearities of the system as the parts of T_L. Therefore, it is important to estimate T_L in real time for achieving good performances of a PMSM system.

When estimating T_L, it is supposed that both B and J have been estimated accurately, i.e., $\hat{B}=B$ and $\widehat{J}=J$ in (5). Therefore, we can update the control strategy (17) as

$$\dot{u}_2+Tu_2=v \tag{36a}$$

$$v=\left(\frac{\hat{J}_0 q}{\beta p}\right)\dot{e}_2^{2-p/q}+(K_{dL}+K_{Tu}+\eta)\operatorname{sgn}(s). \tag{36b}$$

If a TSM observer has been designed based on Theorem 1 and the error system (13) has converged to zero along $s=0$ in finite time, the estimation of $T_L(t)$ can be obtained as follows from (25) because of $\Delta J_0=0$ and $\Delta B_0=0$:

$$\hat{T}_L(t)=-u_2(t). \tag{37}$$

From (37), it can be seen that $T_L(t)$ can be estimated in real time because of the smooth $u_2(t)$. The gain of the switch function in (36b) can be designed to be very high for guaranteeing the robustness, while the equivalent low-pass filter in (36a) can

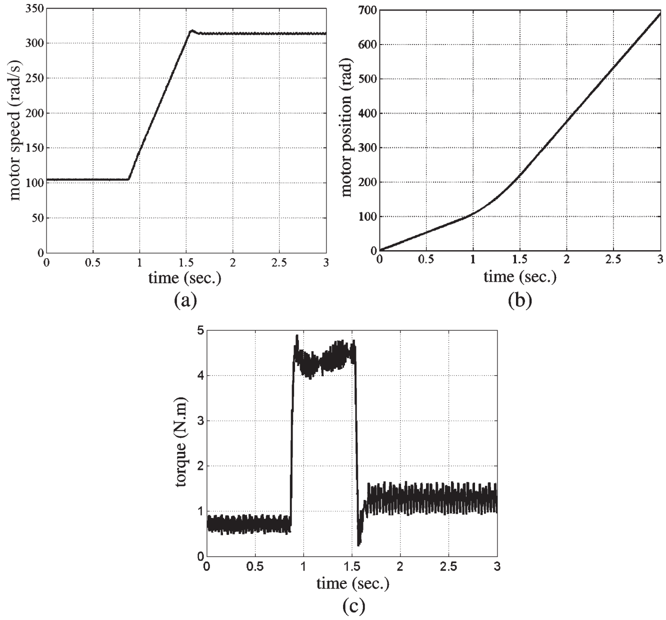

Fig. 4. Experimental results. (a) Motor speed. (b) Motor position. (c) Driving torque.

soften $v(t)$ and produce a smooth signal $u_2(t)$, which can be directly used for estimating $T_L(t)$.

When the operation condition changes, the proposed method can estimate the mechanical parameters and update the controller's parameters based on the present operation condition. This guarantees that the PMSM system will keep the desired performances for different operation conditions.

V. Experimental Results

The proposed method in this paper has been tested on a practical high-precision machine tool. The goal of the experiments is to estimate the mechanical parameters of the permanent-magnet spindle motor of the machine tool.

According to Theorem 1, an observer is designed with the following parameters: $\beta = 1, p = 5, q = 3, T = 1$, and $\eta = 10$.

The experimental measurements of the motor speed, the position, and the driving torque are shown in Fig. 4(a)–(c). The parameter estimation results are shown in Figs. 5–8. The estimation of B is displayed in Fig. 5. There are four different crude estimations of the true parameter of B, i.e., $\hat{B}_0 = 0.1\ B$, $0.5\ B$, $2\ B$, and $10\ B$, corresponding to Fig. 5(a)–(d). It can be seen that all the estimation curves converge to the true value, which means that the proposed method requires a much cruder estimation. Similarly, the estimations of J are shown in Fig. 6 for four different crude estimations, i.e., $\hat{J}_0 = 0.1\ J, 0.5\ J, 2\ J$, and $10\ J$, corresponding to Fig. 6(a)–(d). It can also be seen that all the estimation curves of J for these four different initial values converge to the true value. The sliding-mode surface s is displayed in Fig. 7. It can be seen that s is forced to stay in the area near zero by the control of the observer. The estimation of T_L is depicted in Fig. 8. It should be noted that the estimation of T_L is implemented in real time and can be used for disturbance rejection in a PMSM control system.

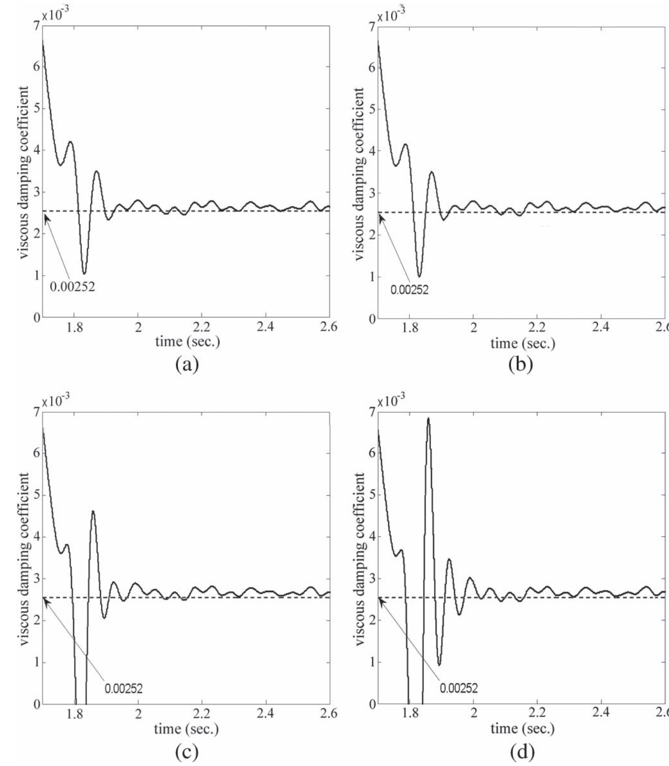

Fig. 5. Estimation of B. (a) $\hat{B}_0 = 0$. (b) $\hat{B}_0 = 0.1\ B$. (c) $\hat{B}_0 = 20\ B$. (d) $\hat{B}_0 = 30\ B$.

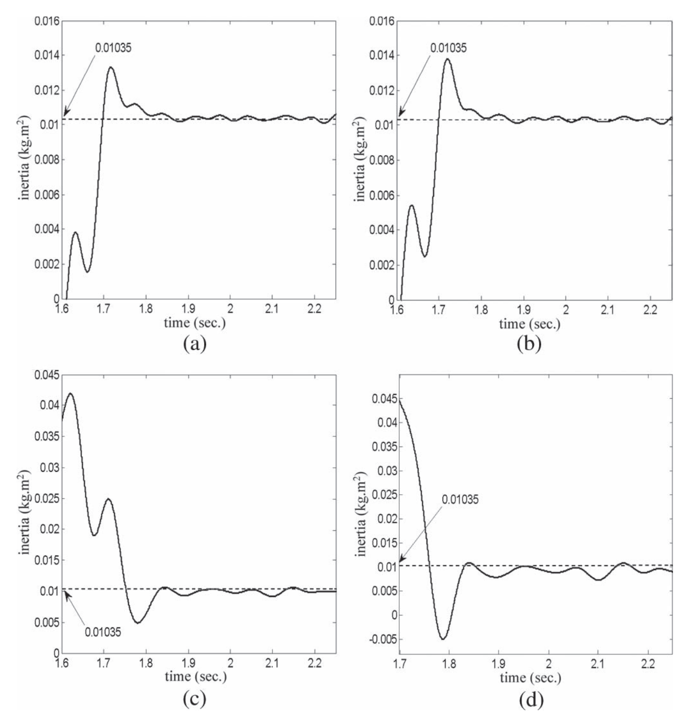

Fig. 6. Estimation of J. (a) $\hat{J}_0 = 0.01\ J$. (b) $\hat{J}_0 = 0.1\ J$. (c) $\hat{J}_0 = 2\ J$. (d) $\hat{J}_0 = 5\ J$.

From the aforementioned experimental results, it can be seen that the estimations of all these mechanical parameters converge to their true values, which proves the effectiveness of the proposed method. In addition, two important summaries for

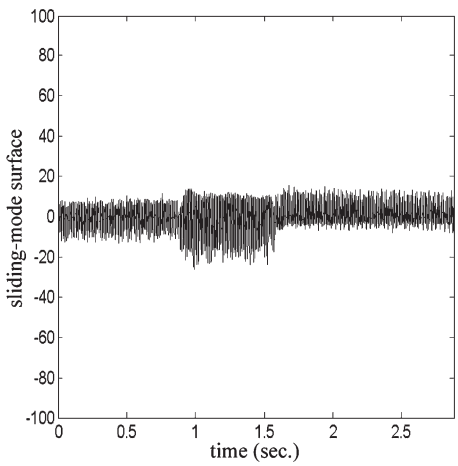

Fig. 7. Sliding-mode.

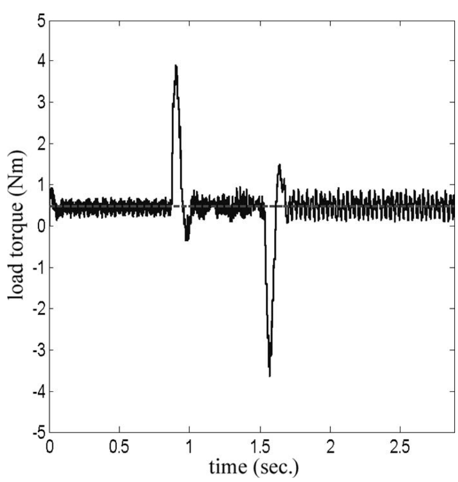

Fig. 8. Estimation of load torque.

parameter estimation can be obtained: 1) the crude estimation of B in the observer (5) should be small, even zero; and 2) the crude estimations of J in the observer (5) should also be small so that the observer (5) can have faster dynamic responses than that of the practical PMSM control system.

VI. Conclusion

This paper has proposed a TSM observer for estimating the mechanical parameters of a PMSM system used in complex mechanical systems. A novel TSM is utilized to guarantee the global finite-time convergence of the observer. The parameter estimation can be realized using the second-order sliding-mode technique. Some experiments have been carried out in a practical CNC machine tool. All three mechanical parameters of the spindle motor system have been estimated successfully with good accuracy. The mechanical model of the motor system in a practical CNC machine tool has been established and compared to the practical measurements. The results further demonstrate the effectiveness of the proposed method. The advantages of the proposed method can be described as follows: 1) the gain of the switch function in the SMC could be set to a high value to guarantee the robustness of the observer; 2) the high-order sliding-mode based mechanism can produce a smooth control signal of the observer, which can be directly used for the parameter estimation; 3) the effect of the equivalent low-pass filter in the control strategy can be properly controlled based on the requirements; and 4) the time-varying load torque can be estimated in real time. The future work is to apply the proposed method to the motor control for yielding better dynamic performance.

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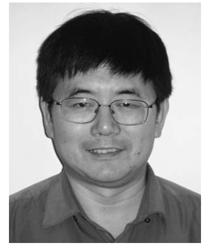

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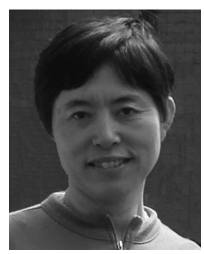

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