

Gain-Adaptive Terminal Higher-Order Sliding Mode Observer with Super-Twisting Algorithm for Sensorless Control of SPMSM

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ABSTRACT: To overcome bandwidth-accuracy trade-offs in sensorless surface-mounted permanent magnet synchronous motor (SPMSM) drives, this study addresses the limitations of traditional observers. Conventional first-order sliding-mode observer (SMO) inherently exhibits high-frequency chattering due to discontinuous switching functions. To smooth the estimated back-EMF, a low-pass filter (LPF) is typically appended as a remedy; however, this filtering induces speed-dependent phase lag during medium- and high-speed operations, whereas its impact at low speeds is negligible. Although conventional higher-order model-based SMO (HOSMO) can better attenuate chattering, a lower cutoff frequency inherently compromises dynamic tracking precision due to increased phase lag. To overcome these challenges, the proposed scheme substitutes filter-dependent laws with a second-order super-twisting algorithm (STA), ensuring continuity of the control signal and zero phase lag. Furthermore, a state-dependent adaptive tuning mechanism based on a continuous nonlinear barrier function was developed. This adaptive law dynamically boosts observer gains to suppress transient perturbations and contracts them at a steady state to minimize chattering. Comprehensive simulations and experimental verifications demonstrated that the proposed gain-adaptive super-twisting higher-order SMO (GAST-HOTSOMO) significantly reduced harmonic distortion, restricted estimation errors, and accelerated dynamic recovery compared to conventional methods.

1. INTRODUCTION

Surface-mounted permanent magnet synchronous motor (SPMSM) is favored in high-performance industrial drives because of its high efficiency and superior torque linearity [1]. Conventional field-oriented control (FOC) relies heavily on mechanical sensors to acquire critical rotor information. However, physical sensors increase hardware costs and spatial volume while compromising system reliability under harsh conditions, such as severe vibrations and thermal drifts [2, 3]. Sensorless control technology has gained prominence. Among the current methodologies, model-based observation remains the most mature and effective solution for seamless, real-time rotor tracking across medium- and high-speed ranges [4–6].

Within position sensorless frameworks, observer performance is pivotal to a drive system. Various estimation methods have been explored, including model predictive observer [7], extended state observer [8, 9], extended Kalman filter [10], and sliding mode observer (SMO) [11–14]. SMO, in particular, offers strong robustness and fast convergence, making it the preferred choice for SPMSM applications. Nevertheless, conventional SMO faces limitations: 1) the discontinuous switching function induces high-frequency chattering, requiring an LPF for signal smoothing that subsequently introduces speed-dependent phase lag [15]; 2) linear sliding surfaces preclude finite-time convergence, leaving steady-state deviations

tions [16]; and 3) fixed, conservative gains force a dilemma between dynamic speed and ripple suppression, compromising overall performance.

First, to bypass LPF and fixed-gain issues, researchers adopted a higher-order model-based sliding observer (HOSMO) for direct, continuous back-EMF extraction [17]. Nevertheless, their fixed gains remain overly conservative, necessitating an unavoidable trade-off between the transient response and steady-state chattering. To mitigate this tuning dilemma, gain-adaptive (GA) mechanisms have been explored [18–20]. However, such designs are predominantly confined to sliding mode controllers or low-order observers and are rarely extended to HOSMO.

Secondly, regarding finite-time convergence, Ref. [21] adaptively adjusts reaching gains based on system states, successfully accelerating tracking rates and reducing steady-state estimation errors. Nevertheless, the capacity of such reaching law schemes to enforce finite-time convergence under complex nonlinear time-varying disturbances remains insufficient. To address this, a terminal sliding mode observer (TSMO) was introduced to enforce finite-time convergence [22, 23]. However, their practical deployment is hindered by singularity issues and their sensitivity to high-frequency noise. Although a second-order super-twisting SMO (ST-SMO) was proposed in [24] to mitigate chattering, its linear sliding surface underutilizes nonlinear dynamics. Furthermore, while the advanced higher-order model-based terminal sliding mode observer (HOTSOMO)

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in [25] guarantees singularity-free, finite-time convergence, its gains must be sufficiently large to strictly fulfill the sliding mode conditions. Consequently, this fixed-gain HOTSMO inevitably induces significant overshoots and violent speed oscillations during dynamic transients, thereby jeopardizing the closed-loop stability of the drive system it is used.

Therefore, to resolve the performance trade-off in conventional observers, this study proposes a real-time gain-adaptive higher-order terminal sliding mode observer (GAST-HOTSMO) for SPMSM's sensorless control. By embedding sliding surface functions into control coefficients, the observer gains seamlessly self-adjust with tracking errors, suppressing steady-state chattering without sacrificing transient stability. This study's main contributions are summarized as follows:

1) Integrated Non-filtering: A GAST-HOTSMO topology integrating a terminal sliding surface with the Super-Twisting algorithm is proposed, enabling fast finite-time convergence and continuous output without LPF-induced phase lag.

2) Barrier-Function-Based Gain Adaptation: A barrier-function adaptive scheme is incorporated to dynamically scale gains without requiring prior knowledge of disturbance bounds, suppressing steady-state noise while ensuring transient robustness.

3) Comprehensive Theoretical and Experimental Validation: Rigorous Lyapunov stability proofs and Digital Signal Processor (DSP)-based experimental tests confirm that this synergistic integration effectively resolves the bandwidth-precision trade-off of the conventional SMO.

2. MODELING AND SYSTEM DESCRIPTION

2.1. Mathematical Modeling of SPMSM

In a stationary α - β reference frame, the SPMSM's electrical dynamics can be characterized by the following current state equations:

$$\frac{d}{dt} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} -\frac{R_s}{L_s} & 0 \\ 0 & -\frac{R_s}{L_s} \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \frac{1}{L_s} \begin{bmatrix} u_\alpha - e_\alpha \\ u_\beta - e_\beta \end{bmatrix} \quad (1)$$

where u_α , u_β and i_α , i_β are the stator voltages and currents, respectively; R_s and L_s denote the resistance and inductance, respectively. The back-EMF components e_α and e_β are defined as:

$$\begin{bmatrix} e_\alpha \\ e_\beta \end{bmatrix} = \omega_e \psi_f \begin{bmatrix} -\sin \theta_e \\ \cos \theta_e \end{bmatrix} \quad (2)$$

where ω_e , θ_e , and ψ_f represent the electrical angular speed, rotor position, and flux linkage, respectively.

Equation (1) can be compactly represented in the matrix form as follows:

$$\frac{d\mathbf{i}}{dt} = \mathbf{A}\mathbf{i} + \mathbf{B}(\mathbf{u} - \mathbf{e}) \quad (3)$$

where $\mathbf{i} = [i_\alpha \ i_\beta]^T$, $\mathbf{u} = [u_\alpha \ u_\beta]^T$, $\mathbf{e} = [e_\alpha \ e_\beta]^T$, $\mathbf{A} = a_0\mathbf{I}$, $\mathbf{B} = b_0\mathbf{I}$, where $\mathbf{I}$ is the 2×2 identity matrix, and $a_0 = -R_s/L_s$, $b_0 = 1/L_s$.

By considering the back-EMF $\mathbf{e}$ in (3) as an extended state, the SPMSM's extended mathematical model can be expressed as:

$$\frac{d}{dt} \begin{bmatrix} \mathbf{i} \\ \mathbf{e} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ 0 & \mathbf{A}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{i} \\ \mathbf{e} \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ 0 \end{bmatrix} \mathbf{u} \quad (4)$$

where $\mathbf{A}_{11} = a_0\mathbf{I}$, $\mathbf{A}_{12} = -b_0\mathbf{I}$, $\mathbf{A}_{22} = \omega_e\mathbf{J}$, and $\mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$ is the orthogonal rotation matrix.

2.2. FOC-Based Sensorless SPMSM Drives

Figure 1 shows the FOC-based sensorless SPMSM drive with a standard cascade double-loop structure. The rotor position is obtained via two cascaded stages: SMO for back-EMF estimation, followed by a quadrature PLL for speed/position calculation. To achieve a high-precision estimation, this study proposes an enhanced SMO framework that overcomes limitations of conventional topologies.

3. CONVENTIONAL SMO AND ISSUES

3.1. Conventional First-Order SMO

Based on the SPMSM mathematical model defined in (1), the first-order SMO structure is formulated as:

$$\frac{d\hat{\mathbf{i}}}{dt} = \mathbf{A}\hat{\mathbf{i}} + \mathbf{B}(\mathbf{u} - \mathbf{z}_i) \quad (5)$$

where “ $\hat{\cdot}$ ” denotes the estimated value; $\mathbf{z}_i = k_s \text{sgn}(\mathbf{i})$ represents the discontinuous observer switching law; k_s is the switching gain. The discontinuous switching function in conventional first-order SMOs inherently excites high-frequency chattering. To attenuate these oscillations and extract smooth back-EMF signals, a low-pass filter (LPF) with a cutoff frequency ω_c is conventionally cascaded in series:

$$G(s) = \frac{\omega_c}{s + \omega_c} \quad (6)$$

When the motor operates at an electrical angular speed ω_e , this filtering stage induces speed-dependent phase lag and magnitude attenuation, expressed as:

$$\phi(\omega_e) = -\arctan\left(\frac{\omega_e}{\omega_c}\right), \quad A(\omega_e) = \frac{\omega_c}{\sqrt{\omega_e^2 + \omega_c^2}} \quad (7)$$

This phase lag directly yields an equivalent rotor position estimation offset $\Delta\theta_e \approx -\theta(\omega_e)$, causing severe performance degradation under medium- and high-speed conditions, whereas its influence at low speeds remains minor.

It should be noted that LPF is a post-processing signal processing unit cascaded with an SMO, rather than an integrated observer dynamic filter. The dynamic degradation induced by filtering highly depends on its bandwidth design. Specifically, configuring a high cutoff frequency ($\omega_c \gg \omega_e$) yields negligible phase lag and minor impacts on dynamic performance, yet

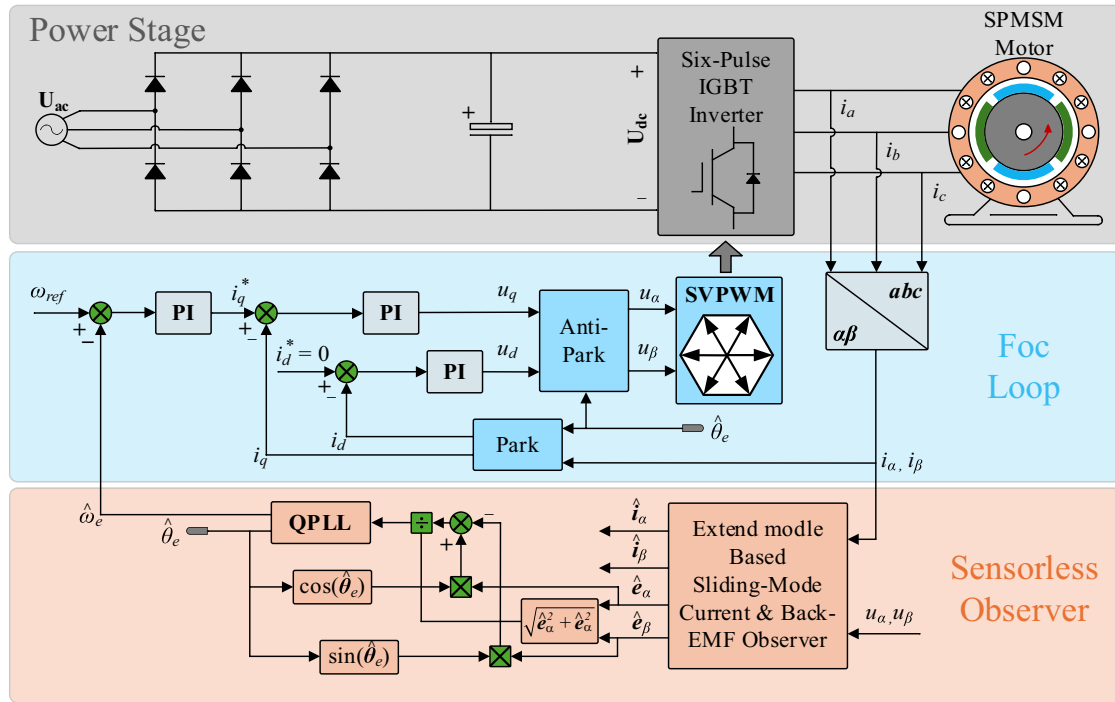


FIGURE 1. Block diagram of FOC-based sensorless drives for SPMSM.

leaves residual mid-to-high frequency chattering. Conversely, employing a low cutoff frequency ($\omega_c \ll \omega_e$) or higher-order filtering structure effectively smooths the estimated back-EMF, but introduces substantial phase lag that severely degrades dynamic position and speed tracking accuracy. Consequently, conventional cascaded filtering approaches inherently suffer from an intractable trade-off between chattering suppression and dynamic responsiveness.

3.2. High-Order Model-Based SMO (HOSMO)

To fully exploit motor dynamics, based on plant dynamics in (4), the extended-state SMO is formulated as:

$$\frac{d}{dt} \begin{bmatrix} \hat{\mathbf{i}} \\ \hat{\mathbf{e}} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ 0 & \hat{\mathbf{A}}_{22} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{i}} \\ \hat{\mathbf{e}} \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ 0 \end{bmatrix} \mathbf{u} - \begin{bmatrix} \mathbf{z}_i \\ \mathbf{z}_e \end{bmatrix} \quad (8)$$

where $\hat{\mathbf{A}}_{22} = \hat{\omega}_e \mathbf{J}$, $[\mathbf{z}_i \ \mathbf{z}_e]^T = \mathbf{K} \text{sgn}(\mathbf{s})$, where $\mathbf{z}_e$ represents the control law for back-EMF; sliding-mode surface

$$\mathbf{s} = [\hat{i}_\alpha - i_\alpha \ \hat{i}_\beta - i_\beta]^T, \mathbf{K} = \begin{bmatrix} b_0 l & 0 & -m & 0 \\ 0 & b_0 l & 0 & -m \end{bmatrix}^T,$$

where l and m are the extended SMO gains.

By subtracting (4) from (8), error dynamics and back-EMF estimation error are derived as follows:

$$\dot{\tilde{\mathbf{x}}} = \mathbf{A} \tilde{\mathbf{x}} - \mathbf{z} \quad (9)$$

$$\tilde{\mathbf{e}} = \mathbf{A}_{12}^{-1} (\dot{\tilde{\mathbf{i}}} - \mathbf{A}_{11} \tilde{\mathbf{i}} + \mathbf{z}_i) \quad (10)$$

where “ $\sim$ ” denotes the error value $\tilde{\mathbf{x}} = [\tilde{\mathbf{i}} \ \tilde{\mathbf{e}}]^T$, and

$\mathbf{z} = [\mathbf{z}_i \ \mathbf{z}_e]^T$; $\tilde{\mathbf{i}} = \hat{\mathbf{i}} - \mathbf{i}$ and $\tilde{\mathbf{e}} = \hat{\mathbf{e}} - \mathbf{e}$ are the stator current and back-EMF errors, respectively

Equation (10) indicates that even if $(\mathbf{s} = \tilde{\mathbf{i}} = 0)$ is achieved via the control law $\mathbf{z}_i$ defined in Section 3.1, the discontinuous switching signal prevents the current error derivative $\dot{\tilde{\mathbf{i}}}$ from disappearing.

Consequently, the back-EMF error $\tilde{\mathbf{e}}$ cannot converge to zero in a finite time, leading to persistent chattering and estimation offsets. This highlights that model extension alone is insufficient; superior observer performance necessitates a more advanced sliding manifold and continuous reaching law.

3.3. HOSMO

To resolve the convergence and chattering issues in (10), an HOSMO was proposed in [25], incorporating a nonlinear terminal sliding surface $\mathbf{s}$:

$$\mathbf{s} = \frac{d\tilde{\mathbf{i}}}{dt} + \alpha |\tilde{\mathbf{i}}|^\gamma \text{sgn}(\tilde{\mathbf{i}}) \quad (11)$$

where $\alpha > 0$ and $0 < \gamma < 1$ are constants. Meanwhile, a high-order control law $\mathbf{z}_i$ is also proposed:

$$\mathbf{z}_i = -\alpha |\tilde{\mathbf{i}}|^\gamma \text{sgn}(\tilde{\mathbf{i}}) - \mathbf{u}_n \quad (12)$$

$$\frac{d\mathbf{u}_n}{dt} + \omega_f \mathbf{u}_n = k \text{sgn}(\mathbf{s}) \quad (13)$$

where $\mathbf{u}_n = [u_{n\alpha} \ u_{n\beta}]^T$ is the continuous control component, and k and ω_f are gain parameters.

Despite its advantages, HOSMO has two critical limitations. First, the Laplace transform of (13) reveals its filtering characteristics:

$$U_n(s) = \frac{\omega_c}{s + \omega_c} \cdot [k \text{sgn}(\mathbf{s})] \quad (14)$$

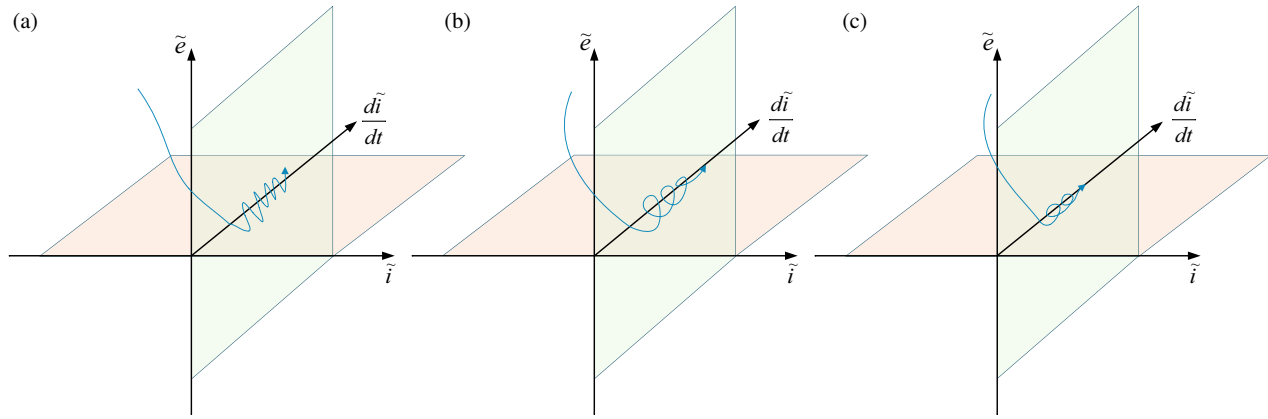


FIGURE 2. State error trajectories and sliding mode manifolds of different observation mechanisms: (a) First-order SMO, (b) HOTSMO, and (c) the proposed GAST-HOTSMO.

where ω_c denotes the observer's equivalent cutoff frequency, inducing a speed-dependent phase lag $\phi = -\arctan(\omega_e/\omega_c)$ and degrading the estimation accuracy.

Second, to guarantee the observer's Lyapunov stability, switching gains k and m must satisfy the following boundary conditions:

$$\begin{cases} k > \max(|A_{11}D| + |\omega_c u_{n\alpha}|, |A_{11}D| + |\omega_c u_{n\beta}|) \\ m > \max(|\hat{\omega}_e \tilde{e}_\alpha|, |\hat{\omega}_e \tilde{e}_\beta|) \end{cases} \quad (15)$$

where D represents the upper bound of the current error derivative.

Selecting these gain coefficients presents a critical trade-off that restricts HOTSMO's performance. To ensure the observer's stability across the entire operating range, k and m must be chosen as fixed values large enough to cover the maximum possible back-EMF error and electrical angular speed.

However, these fixed gain settings impose a fundamental trade-off: large coefficients satisfy stability condition (14) at the cost of intense chattering and degraded estimation accuracy in the PLL circuit. Conversely, smaller gains suppress chattering but risk violating the reaching condition, thereby sacrificing observer stability. This conflict between stability and dynamic performance underscores the necessity of an adaptive gain-tuning mechanism that dynamically balances precision and robustness based on real-time observation states. State error trajectories and sliding-mode manifolds of the three observation methods are compared in Fig. 2.

4. PROPOSED GAIN-ADAPTIVE SUPER-TWISTING HOTSMO (GAST-HOTSMO)

4.1. Structure of the Proposed GAST-HOTSMO

To overcome phase lag and chattering issues in a conventional HOTSMO, a novel adaptive terminal SMO based on GAST-HOTSMO is proposed. By substituting the LPF-based control law in (11) with the second-order super-twisting algorithm (STA), the proposed observer for the SPMSM can be formu-

lated as:

$$\frac{d}{dt} \begin{bmatrix} \hat{\mathbf{i}} \\ \hat{\mathbf{e}} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ 0 & \hat{\mathbf{A}}_{22} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{i}} \\ \hat{\mathbf{e}} \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ 0 \end{bmatrix} \mathbf{u} - \begin{bmatrix} z_i^{STA} \\ z_e \end{bmatrix} \quad (16)$$

where $\mathbf{z}_i^{STA} = [z_{i\alpha}^{STA} \ z_{i\beta}^{STA}]^T$ is the super-twisting control law designed for the stator current observer. To ensure the finite-time convergence of both the current error and its derivative, $\mathbf{z}_i^{STA}$ is coupled with the terminal sliding manifold $\mathbf{s}$ defined in (11):

$$\begin{cases} \mathbf{z}_i^{STA} = -k_1(s, t) |\mathbf{s}|^{1/2} \text{sgn}(\mathbf{s}) + \mathbf{v} \\ \mathbf{v} = -k_2(s, t) \text{sgn}(\mathbf{s}) \end{cases} \quad (17)$$

where $\mathbf{v} = [v_\alpha \ v_\beta]$ is an auxiliary state vector, and $\lambda > 0$, $\alpha > 0$ are positive gains to be designed. $k_1(s, t)$ and $k_2(s, t)$ are the time-varying observer gains determined by the adaptive law in the next subsection.

In contrast to the filter-based control law in (13), the STA in (17) ensures control signal continuity owing to its second-order dynamics, thereby eliminating the need for an external cascading filter. This fundamental structural divergence can be elucidated by examining the operational mechanisms of the switching term $\text{sgn}(s)$:

$$\mathbf{z}_i^{STA}(s) = (k_1(s, t) \frac{1}{\sqrt{|\mathbf{s}|}} + \frac{k_2(s, t)}{\mathbf{s}}) \cdot [\text{sgn}(\mathbf{s})] \quad (18)$$

As shown in (18), the STA integrates the discontinuous term within its internal proportional-integral structure. This embedding mechanism allows the proposed GAST-HOTSMO to suppress high-frequency chattering while maintaining a zero-phase-lag characteristic, effectively resolving the bandwidth-accuracy trade-off identified in (15). Furthermore, the nonlinear gain $k_1(s, t) |\mathbf{s}|^{1/2}$ ensures that both the sliding variable s and its derivative $\dot{s}$ vanish in finite time, enabling a smooth and precise back-EMF estimation even under high-speed operation.

4.2. Gain-Adaptive Law Design

To bridge the gap between robustness and estimation precision, fixed observer gains l and m in (15) are dynamically regulated by a state-dependent adaptive mechanism. Unlike conventional switching-type adaptive laws, a continuous nonlinear mapping based on the barrier function is designed as:

$$k_1(s, t) = \frac{\bar{k}_1}{1 - \mu|s|^p}, \quad k_2(s, t) = \beta k_1(s, t) \quad (19)$$

where $\bar{k}_1 > 0$ denotes the nominal base gain; μ defines the error tolerance boundary; $p > 0$ is the curvature coefficient that regulates the adaptation sensitivity; and β is the gain ratio factor.

By substituting (19) into the stability criterion (15), the dynamic reaching condition of the proposed GAST-HOTSMD can be reformulated as:

$$\begin{cases} \frac{\bar{k}_1}{1 - \mu|s|^p} > \max(|A_{11}D| + |\omega_f u_{n\alpha}|, |A_{11}D| + |\omega_f u_{n\beta}|) \\ m > \max(|\hat{\omega}_e \tilde{e}_\alpha|, |\hat{\omega}_e \tilde{e}_\beta|) \end{cases} \quad (20)$$

Equation (20) illustrates the self-tuning essence of the proposed method. When external disturbances drive the sliding variable s toward the boundary $\mu^{-1/p}$, the denominator $(1 - \mu^{-1/p})$ vanishes, triggering a rapid nonlinear boost in gains to satisfy the reaching condition without prior knowledge of the perturbation bound D . Conversely, as the system approaches steady state, gains automatically contract to the nominal base value $\bar{k}_1$. Because $\bar{k}_1$ is assigned, the offsets are effectively minimized. Consequently, integrating (19) into (17) achieves an optimal balance between dynamic robustness and estimation precision.

In summary, the GAST-HOTSMD architecture achieves enhanced performance via synergistic integration: the terminal sliding surface ensures fast finite-time error convergence; the Super-Twisting algorithm eliminates chattering without needing low-pass filtering; and the barrier function dynamically scales gains to handle unknown disturbances. An implementation procedure of the proposed GAST-HOTSMD in each discrete-time control step is illustrated in Fig. 3. The overall structure of the proposed GAST-HOTSMD is shown in Fig. 4.

The stability of the proposed GAST-HOTSMD is established via nonlinear sliding mode analysis. By substituting (17) into (11), the resulting sliding dynamics can be expressed as:

$$\begin{cases} \dot{s} = -k_1(s, t) |s|^{1/2} \text{sgn}(s) + v + \phi_1(s, t) \\ \dot{v} = -k_2(s, t) \text{sgn}(s) + \phi_2(s, t) \end{cases} \quad (21)$$

In (21), lumped perturbation terms $\phi_1(s, t)$ and $\phi_2(s, t)$ explicitly capture motor parameter mismatches, inverter nonlinearities, DSP discretization sampling delays, and load disturbances. Specifically, they are expanded as:

$$|\phi_1| = \frac{1}{L_s} \left(\Delta R_s i + \Delta L_s \frac{di}{dt} + u_{dead} \right) + O(T_s) \quad (22)$$

$$|\phi_2| = \frac{de}{dt} + \Delta A_{22} \hat{e} \quad (23)$$

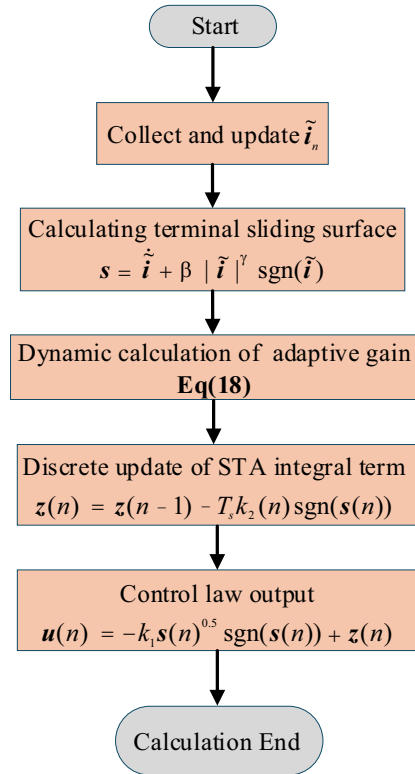


FIGURE 3. Implementation flowchart of the proposed real-time GAST-HOTSMD algorithm in a discrete-time control step.

where ΔR_s and ΔL_s denote stator resistance and inductance estimation errors; u_{dead} represents the inverter dead-time voltage distortion; T_s is the DSP sampling period introducing discretization delay $O(T_s)$; and de/dt encapsulates the rapid back-EMF variations induced by load torque transients. Since the physical variables (i , di/dt , e , de/dt) and physical parameter errors in actual SPMSM drives are physically bounded, there exist finite positive constants δ_1 and δ_2 such that $|\phi_1(s, t)| \leq \delta_1 |s|^{1/2}$ and $|\phi_2(s, t)| \leq \delta_2$ hold across all operating conditions. To reformulate (21) into a linear structure, define the state vector $\xi = [\xi_1, \xi_2]^T = [|s|^{1/2} \text{sgn}(s), v]^T$ where ξ_1 represents the transformed sliding variable that linearizing the STA dynamics. The dynamics of ξ can be expressed as:

$$\dot{\xi} = \frac{1}{|\xi_1|} \mathbf{A}(s, t) \xi + \mathbf{B} \Gamma(t) \quad (24)$$

where the system matrix $\mathbf{A}(s, t)$ disturbance distribution matrix $\mathbf{B}$ and perturbation vector $\Gamma(t)$ are defined as:

$$\begin{aligned} \mathbf{A}(s, t) &= \begin{bmatrix} -\frac{1}{2} k_1(s, t) & \frac{1}{2} \\ -k_2(s, t) & 0 \end{bmatrix} \\ \mathbf{B} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \\ \Gamma(t) &= \begin{bmatrix} \frac{\phi_1(s, t)}{2|\xi_1|} \\ \phi_2(s, t) \end{bmatrix} \end{aligned} \quad (25)$$

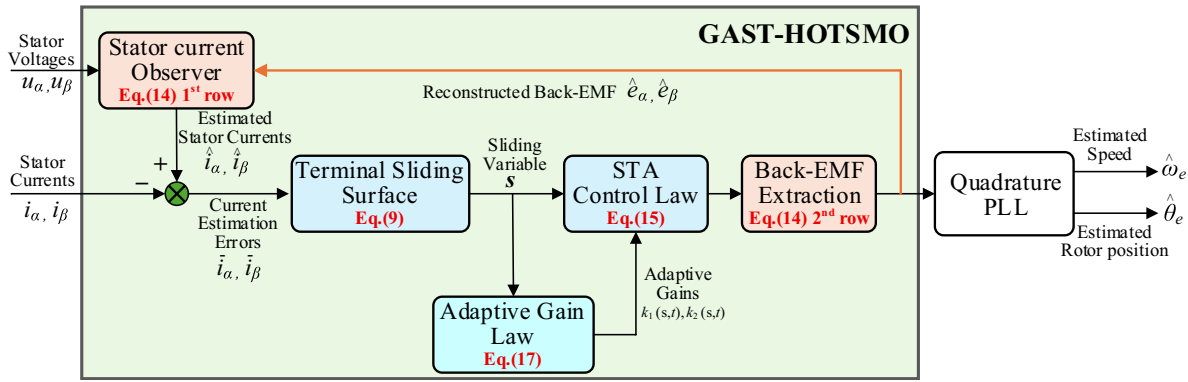


FIGURE 4. Block diagram of the proposed GAST-HOTSMO.

Consider the following candidate Lyapunov function $\mathbf{V}(\xi)$:

$$\mathbf{V}(\xi) = \xi^T \mathbf{P} \xi, \quad \mathbf{P} = \begin{bmatrix} \lambda^2 + 4\zeta & -2\zeta \\ -2\zeta & 1 \end{bmatrix} \quad (26)$$

where $\mathbf{P}$ is the symmetric positive-definite matrix λ , and $\zeta > 0$. The time derivative of $\mathbf{V}(\xi)$ along the trajectory of (25) is expressed as follows:

$$\dot{\mathbf{V}}(\xi) = \frac{1}{|\xi_1|} \xi^T (A^T P + P A) \xi + 2\xi^T P B \Gamma \quad (27)$$

Substituting barrier gains $k_1(s, t) = \bar{k}/1 - \mu|s|^p$, $k_2(s, t) = \alpha k_1(s, t)$ from (20) into (27), we define the algebraic Riccati-like term $\mathbf{Q}(s, t)$ as:

$$\mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A} = -\mathbf{Q}(s, t) \quad (28)$$

Given properties of the barrier function in (19), the minimum eigenvalue of $\mathbf{Q}(s, t)$ satisfies:

$$\lambda_{\min}(\mathbf{Q}(s, t)) \geq \frac{\eta}{(1 - \mu|s|^p)^2} \quad (29)$$

where $\eta > 0$. By applying the Rayleigh quotient inequality, (27) is bounded as follows:

$$\dot{\mathbf{V}}(\xi) \leq \frac{1}{|\xi_1|} \lambda_{\min}(\mathbf{Q}) \|\xi_2\|^2 + 2\|\xi\|_2 \|P\|_2 \|\Gamma\|_2 \cdot \|\xi\|_2 \quad (30)$$

where $\|\cdot\|_2$ denotes the Euclidean norm for vectors and the spectral norm for matrices. Since $|\xi_1| \leq \|\xi\|_2 \leq \sqrt{\mathbf{V}/\lambda_{\min}(\mathbf{P})}$, (30) is simplified to the standard finite-time convergence form:

$$\dot{\mathbf{V}}(\xi) \leq -\kappa_1 \mathbf{V}^{1/2} - \kappa_2 \mathbf{V} \quad (31)$$

where $\kappa_1, \kappa_2 > 0$. Equation (31) guarantees that the sliding variable s reaches the manifold $s = 0$ in a finite time $T_r \leq 2\mathbf{V}^{1/2}(0)/\kappa_1$. Once on the manifold, the current error $\tilde{i}$ converges to zero according to the terminal dynamics in (11), thus completing the proof of the first part.

Remark 1 (Well-Definedness and Positive Invariance of Barrier Gain): To ensure that the barrier-function adaptive gain $k_1(s, t)$ in (19) remains strictly well-defined (i.e., avoiding singularity where the denominator becomes zero), the initial sliding variable is set within the boundary domain, i.e.,

$|s(0)| < \mu^{-1/p}$. When external disturbances drive $s(t)$ toward the boundary threshold $\mu^{-1/p} k_1(s, t)$ approaches infinity, generating a strong corrective action that pulls $s(t)$ back into the strictly invariant domain $\Omega_s = \{s \in \mathbb{R}^2 : |s| < \mu^{-1/p}\}$. This dynamic barrier mechanism guarantees that $s(t)$ never reaches or crosses $\mu^{-1/p}$, thereby ensuring that $1 - \mu^p > 0$ strictly holds for all $t \geq 0$. Consequently, the adaptive gain $k_1(s, t)$ is well-defined and bounded throughout real-time digital implementation.

5. SIMULATION RESULTS AND EXPERIMENT VERIFICATION

5.1. Simulation Results

To validate the feasibility and superiority of the proposed GAST-HOTSMO, simulations were conducted in MATLAB/Simulink. The proposed method was compared with the conventional first-order SMO and HOTSMO [25] under identical operating conditions. Detailed parameters of the test motor are listed in Table 1.

TABLE 1. Simulation parameters settings.

Parameters	Symbol/Unit	Values
Stator resistance	R_s/Ω	2.875
dq -axis inductance	L_s/mH	0.1
Number of pole pairs	P_n	4
Rotational inertia	$J/\text{kg} \cdot \text{m}^2$	0.003
Damping coefficient	$B/\text{N} \cdot \text{m} \cdot \text{s}$	0.008
Flux linkage	ψ_f/Wb	0.175
DC voltage	U_{dc}/V	311

To ensure a fair comparison, all observer gains are rigorously tuned based on unified design criteria across the full operating envelope. For the conventional first-order SMO, the switching gain k_s is selected to bound the maximum back-EMF at rated speed, and the LPF cutoff frequency $\omega_c = 400 \text{ rad/s}$ is optimized to balance chattering suppression and phase delay. For the conventional HOTSMO, the fixed gains (k, l, m) are set to satisfy the worst-case boundary condition in (15), guaranteeing global stability during maximum load transients. For the

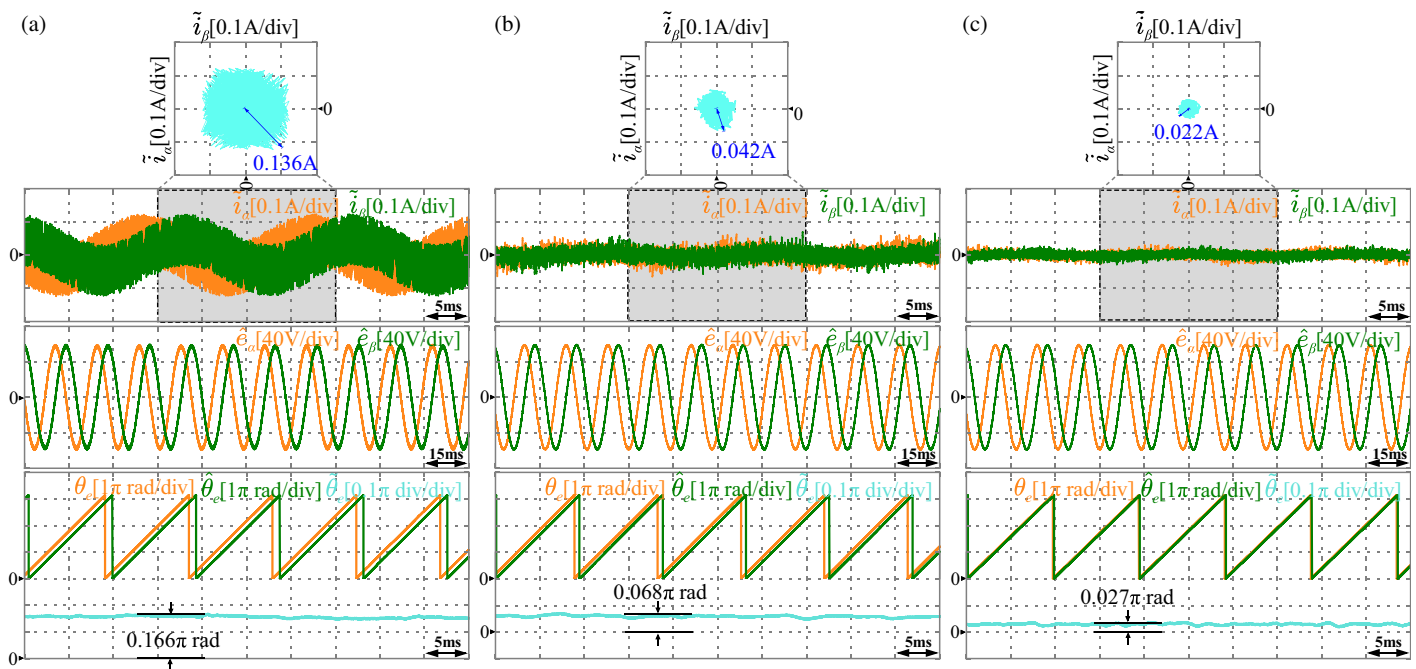


FIGURE 5. Simulation results of three methods at 400 r/min. From top to bottom: stator current estimation error $\tilde{i}$ and its Lissajous, estimated back-EMF $\hat{e}$, and actual, estimated and error of rotor positions $\theta_e, \hat{\theta}_e, \tilde{\theta}_e$. (a) First-order SMO, (b) HOTSMO, and (c) the proposed GAST-HOTSMO.

TABLE 2. Main parameters of the control system.

Control Strategy	Main Parameter Setting Value
First-order SMO	Switching gain $k_s = 15$; LPF cutoff frequency $\omega_c = 400$
HOTSMO	Switching gains $k = 15, l = 400, m = 1$; Cutoff frequency $\omega_c = 400$; Surface gains $\gamma = 7/9, \alpha = 2.5$
GAST-HOTSMO	GA gains $\bar{k}_1 = 1.5, \mu = 0.05, p = 0.05, \beta = 1.5$; Surface gains $\gamma = 7/9, \alpha = 2.5$

proposed GAST-HOTSMO, the nominal base gain $\bar{k}_1$ is deliberately chosen smaller than HOTSMO's fixed gains to suppress steady-state chattering, and dynamic perturbations are handled by the adaptive barrier mechanism. Primary parameters of the three control strategies are summarized in Table 2.

5.1.1. Steady-State Performance Verification

The steady-state estimation accuracy was first validated at a constant speed of 400 r/min. Fig. 5 illustrates the comparative simulation curves of the estimated back-EMF, stator current estimation errors, and rotor position errors for the three methods.

In Fig. 5(a), the conventional first-order SMO current error trajectory converges to the origin but with a wide dispersion (peak error: 0.136 A). High-frequency switching induced severe chattering in the estimated current and back-EMF, causing a substantial rotor position error peak of 0.166π rad.

As shown in Fig. 5(b), the conventional HOTSMO partially suppressed chattering and reduced the peak current error to 0.042 A with residual fluctuations. However, a steady-state position offset of 0.068π rad persists owing to the speed-dependent phase lag of its low-pass filter.

In contrast, the proposed GAST-HOTSMO delivers the highest precision. As shown in Fig. 5(c), the current error trajectory is tightly centered at the origin with a minimal peak error of

0.022 A, restricting the rotor position error to 0.027π rad. This confirms the zero-phase-lag capability of the super-twisting algorithm and continuous barrier adaptive law.

5.1.2. Transient Performance and Robustness Verification

Transient performance and robustness were evaluated at 400 r/min under abrupt load variations. Fig. 6 presents the dynamic response curves of the three observers under a $10\text{ N}\cdot\text{m}$ step-load torque change.

During load switching, the conventional first-order SMO suffers from the most significant fluctuations. The transient position error peak reached 0.277π rad, with a speed deviation of 162 rpm and a settling time of 13.5 ms owing to its fixed gains and chattering. The conventional HOTSMO reduces the transient position error peak to 0.095π rad and speed deviation to 70 rpm, but takes 8.22 ms to recover owing to low-pass filter bandwidth limits.

Conversely, the proposed GAST-HOTSMO minimized deviations, restricting the position error peak to 0.049π rad and speed fluctuation to 42 rpm, while shortening the settling time to 7.13 ms. Under torque transitions, the barrier adaptive law in (17) instantly boosts the observer gains to counteract the perturbation, suppressing both the speed drop and transient tracking errors.

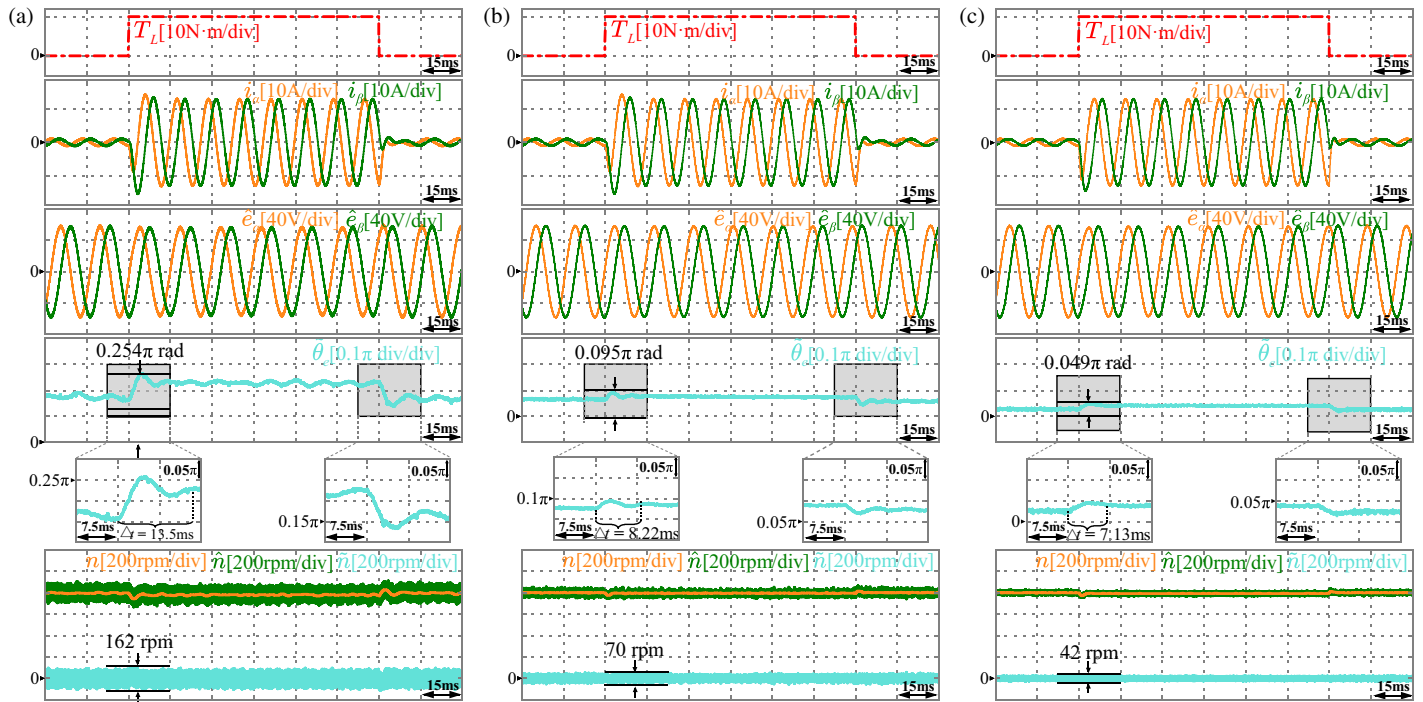


FIGURE 6. Simulation results of three methods under sudden load torque changes at 400 r/min. From top to bottom: load disturbance T_L , stator current estimation error $\tilde{i}_s$, estimated back-EMF $\hat{e}$, estimated rotor positions $\hat{\theta}_e$. (a) First-order SMO, (b) HOTSMO, and (c) the proposed GAST-HOTSMO.

TABLE 3. Simulation performance improvement matrix (compared to first-order SMO baseline).

Observer	Steady Current Error Reduction	Steady Position Error Reduction	Transient Position Error Reduction	Dynamic Speed Suppression	Settling Time Reduction
HOTSMO	69.12%	59.04%	65.70%	56.79%	39.11%
GAST-HOTSMO	83.82%	80.71%	82.31%	74.07%	47.19%

TABLE 4. Comparison of estimation precision and dynamic response.

Observer	Position Error	Settling Time	Interpretation
First-Order SMO	0.166π rad	13.5 ms	Low precision, limited bandwidth
HOTSMO	0.068π rad	8.22 ms	Precision improved, bandwidth still limited
Proposed GAST-HOTSMO	0.027π rad	7.13 ms	High precision with fast response

Quantitative performance improvements in the three observers are presented in Table 3. By evaluating both steady-state error reductions and dynamic transient suppression metrics against the first-order SMO baseline, the extracted matrix reveals that the proposed GAST-HOTSMO achieves the most significant improvement across all key simulation evaluation criteria.

As summarized in Table 4, the simulated and experimental results can be further interpreted from the perspective of the bandwidth-precision trade-off discussed in Section 3. Conventional first-order SMO suppresses chattering by employing an external LPF, whose bandwidth selection inevitably introduces a compromise between estimation precision and dynamic response. Although HOTSMO improves the estimation accuracy, its equivalent LPF characteristic still causes phase lag, limit-

ing achievable dynamic bandwidth. In contrast, the proposed GAST-HOTSMO eliminates the dependence on external filtering through the super-twisting algorithm.

5.2. Experiment Verification

5.2.1. Experimental Setup

To evaluate the practical performance of the proposed control method, an experimental platform was constructed, as shown in Fig. 7. The setup comprised an SPMSM, a DC motor acting as the load dynamometer, a high-precision torque sensor, and a drive control system powered by a TMS320F28335 DSP. The inverter switching frequency is set to 10 kHz with a corresponding 100 μ s pulse width modulation (PWM) carrier period, with which the DSP interrupt cycle is synchronized. A 2500-

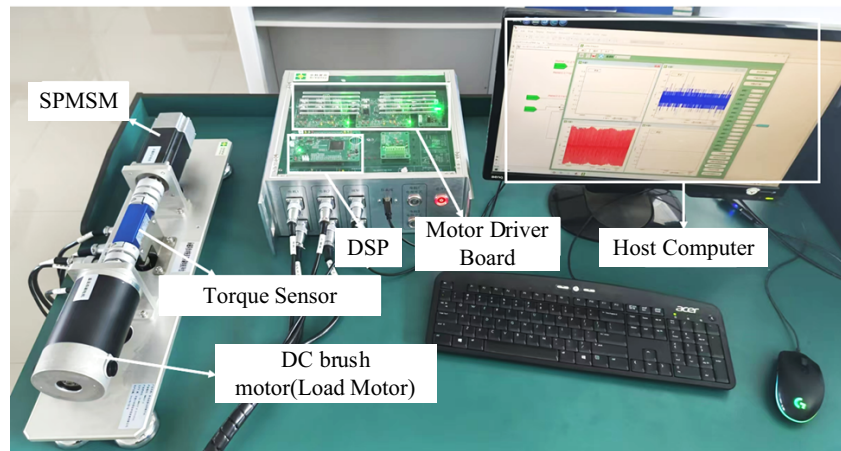
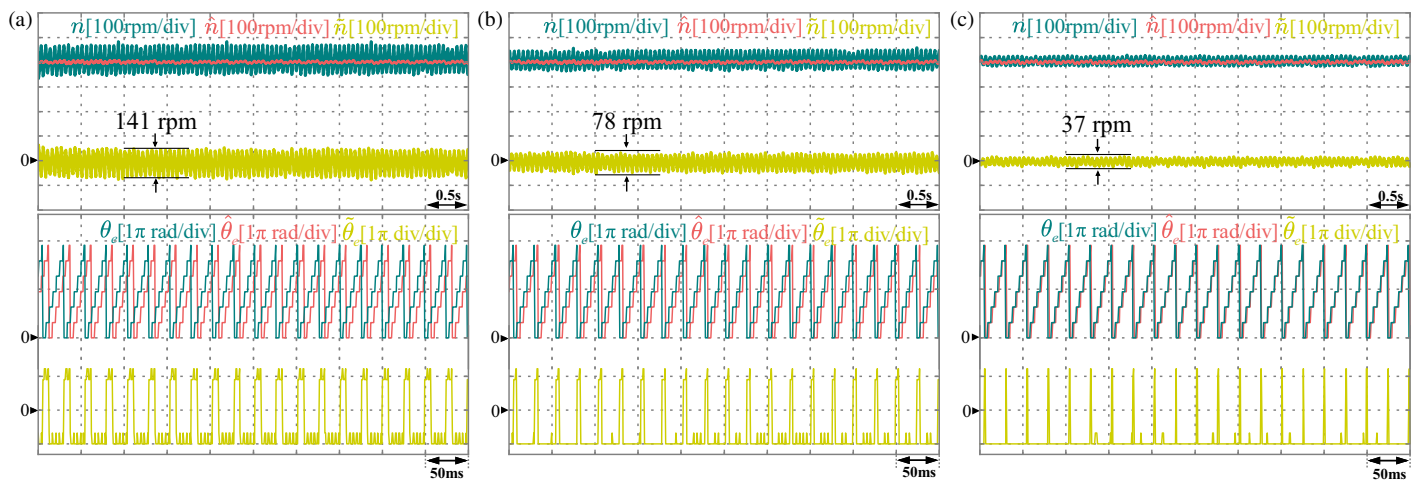


FIGURE 7. Photograph of Experimental platform.

FIGURE 8. Steady-state experimental waveforms of the three observers at a constant speed of 400 r/min. From top to bottom: actual, estimated and error of speed n , $\hat{n}$, $\tilde{n}$, actual, estimated and error of rotor positions θ_e , $\hat{\theta}_e$, $\tilde{\theta}_e$. (a) First-order SMO, (b) HOTSMO, and (c) the proposed GAST-HOTSMO.

line incremental encoder was used for the speed measurement. Control algorithms were automatically generated via Embedded Coder and deployed onto the DSP for real-time execution. The parameter settings for all three control strategies were identical to those used in the simulation tests.

To obtain ground-truth speed and rotor position for sensorless evaluation, the quadrature signal from the 2500-line incremental encoder is decoded via the DSP's enhanced quadrature encoder pulse module (eQEP) with four times pulse multiplication, yielding a high quantization resolution of 10,000 counts per mechanical revolution. The control execution and data acquisition are strictly synchronized with the 10 kHz PWM carrier (100 μ s interrupt cycle), where the eQEP position reading and ADC current sampling are latch-triggered simultaneously to eliminate temporal phase misalignment. The actual speed is calculated using backward difference from eQEP counts and smoothed by a first-order low-pass filter to attenuate pulse quantization noise. Furthermore, the position estimation error $\theta_e = \hat{\theta}_e - \theta_e$ is dynamically normalized within $[-\pi, \pi)$ rad to prevent phase-wrapping discontinuities.

5.2.2. Steady-State Performance Comparison

Steady-state experiments were conducted at 400 r/min to evaluate estimation accuracy under weak back-EMF conditions. As shown in Fig. 8, the conventional first-order SMO exhibits severe speed ripples (141 rpm peak-to-peak), high-frequency chattering, and noticeable phase lag. Although the conventional HOTSMO reduces the speed ripple to 78 rpm and alleviates chattering, a steady-state phase lag remains due to the low-pass filter. In contrast, the proposed GAST-HOTSMO further reduces the speed ripple to 37 rpm while maintaining smooth position estimation and accurate phase tracking. Table 4 quantitatively confirms that the proposed method achieves a 73.76% reduction in steady-state speed ripple over the first-order SMO, outperforming the conventional HOTSMO (44.68%).

5.2.3. Transient Robustness Comparison under Load Disturbances

To verify the dynamic recovery capability and robustness of observers, dynamic experiments were performed at 400 r/min under abrupt load variations. Fig. 9 shows the transient re-

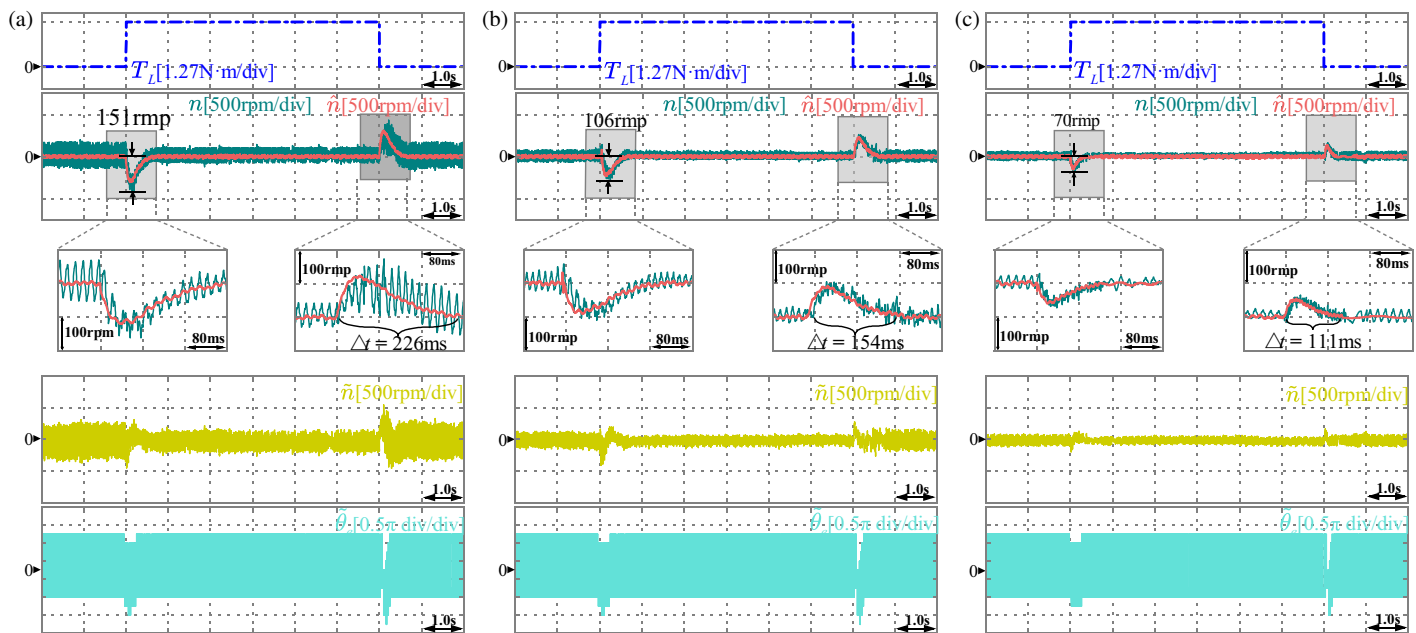


FIGURE 9. Dynamic performance and transient robustness comparison under sudden load torque variations at 400 r/min. From top to bottom: load disturbance T_L , actual and estimated speeds n , $\hat{n}$, error speed $\tilde{n}$, and error rotor positions θ_e . (a) First-order SMO, (b) HOTSMO, and (c) the proposed GAST-HOTSMO.

TABLE 5. Experiment performance improvement matrix (compared to first-order SMO baseline).

Observer	Steady Speed Ripple	Dynamic Speed Drop	Transient Recovery Time
HOTSMO	44.68%	26.49%	31.86%
Proposed GAST-HOTSMO	73.76%	53.64%	50.88%

sponse curves of the three methods when a step-load torque of $1.27 \text{ N} \cdot \text{m}$ is suddenly applied and subsequently removed.

As depicted in Fig. 9(a), the conventional SMO is highly sensitive to external disturbances, exhibiting a pronounced speed drop of 151 rpm and an extended recovery period of 226 ms, along with significant transient position error spikes. In Fig. 9(b), the conventional HOTSMO improves the transient performance, restricting the speed drop to 111 rpm and shortening the recovery time to 154 ms, although noticeable dynamic tracking deviations persist.

Conversely, the proposed GAST-HOTSMO minimizes deviations, as shown in Fig. 9(c). The dynamic speed drop was restricted to 70 rpm, and the settling time was shortened to 111 ms. Under load perturbations, the barrier adaptive law in Equation (18) instantly boosts observer gains to maintain the sliding manifold. Once stabilized, the gains automatically contract to suppress chattering, validating the practical effectiveness of the gain-adaptive mechanism.

Dynamic improvements are summarized in Table 5. Compared with the SMO baseline, the conventional HOTSMO reduced the dynamic speed drop and recovery time by 26.49% and 31.86%, respectively. Meanwhile, the proposed GAST-HOTSMO achieved superior dynamic robustness, delivering a 53.64% reduction in speed drop and a 50.88% reduction in transient recovery time.

5.2.4. Wide-Range Speed Tracking Performance

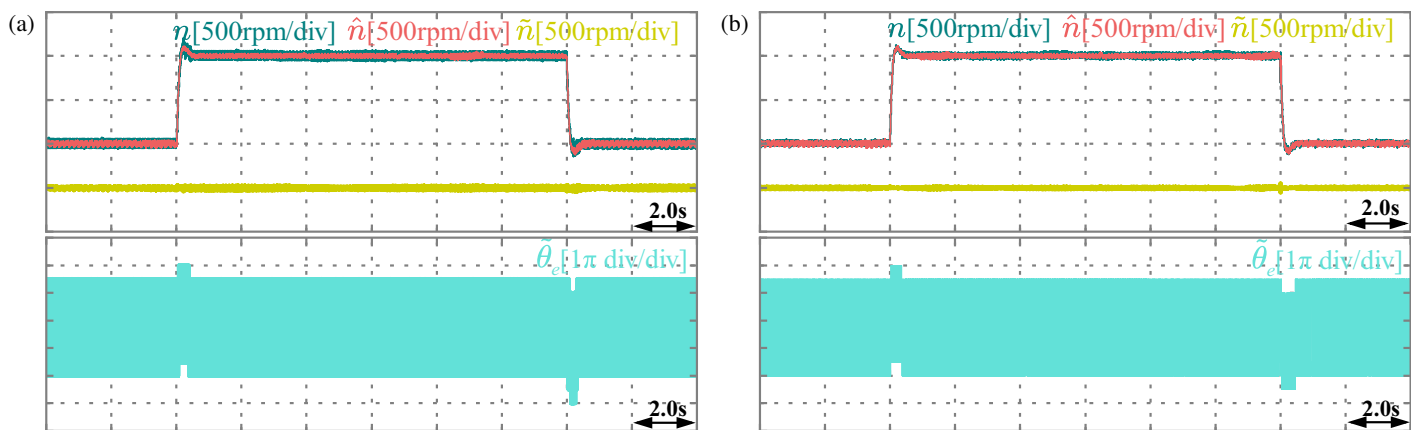
To further validate the stability and tracking capability of the proposed algorithm over a wide operating range, a dynamic speed-stepping experiment was conducted. Fig. 10 shows the experimental results of the proposed GAST-HOTSMO when the speed reference abruptly steps from 500 r/min to 1500 r/min, and subsequently steps back to 500 r/min.

During rapid acceleration and deceleration transients, the estimated speed tracked the actual speed seamlessly with minimal overshoot and zero lag. The rotor position estimation error remains tightly bounded and stabilizes quickly without any divergence or accumulation errors. This successful wide-range speed tracking experiment demonstrates that the proposed GAST-HOTSMO is highly stable under large-scale dynamic operating transitions, proving its strong potential for practical industrial applications.

To rigorously evaluate the computational burden, all control algorithms generated by Embedded Coder are compiled using Texas Instruments Code Composer Studio (CCS) with level-two compiler optimization and deployed on the 150 MHz TMS320F28335 DSP. The real-time execution time of each algorithm within the $100 \mu\text{s}$ PWM interrupt cycle is precisely measured using an internal CPU timer and verified via GPIO pin toggling on a digital oscilloscope. As in Table 6, the execu-

TABLE 6. Computational burden comparison of the three observers.

Observer	Basic Operations	Operation Count	Computation time
First-Order SMO	+, −	6	11.61 μ s
	*, /	12	
HOTSMO	+, −	20	16.51 μ s
	*, /	32	
	sqrt	2	
Proposed GAST-HOTSMO	+, −	22	18.67 μ s
	*, /	37	
	sqrt	3	

**FIGURE 10.** Experimental results of the proposed GAST-HOTSMO under speed reference changes from 500 to 1500 r/min, and then back to 500 r/min. From top to bottom: actual, estimated and error of speed n , $\hat{n}$, $\tilde{n}$, error rotor positions $\hat{\theta}_e$. (a) Under no-load condition and (b) under rated load condition.

tion time of the proposed GAST-HOTSMO is 18.67 μ s, which consumes only 18.67% of the total control period, leaving a comfortable computation margin of over 81% for background tasks and safety protection.

Although the experimental validation is conducted under representative operating conditions, the existing results demonstrate the robustness of the proposed GAST-HOTSMO from both dynamic and steady-state perspectives. Owing to the super-twisting algorithm and the barrier-function-based adaptive gain mechanism, the observer automatically adjusts its gains according to the estimation error, enabling stable operation without manual parameter tuning.

As demonstrated in Fig. 9 and Fig. 10, the proposed observer maintains accurate position estimation during both load disturbances and speed transitions. The adaptive gain mechanism rapidly suppresses transient estimation errors while reducing steady-state chattering after the disturbance disappears. Moreover, eliminating the LPF-dependent estimation mechanism avoids the bandwidth limitation of conventional observers, thereby improving estimation performance over a wide operating speed range.

Theoretical robustness is further supported by the lumped perturbation model in Equation (21), which explicitly considers parameter mismatches, inverter nonlinearities, sampling de-

lays, and load disturbances. Since the experimental platform also contains practical measurement noise, the reported results reflect realistic operating conditions. More comprehensive validation under deliberately introduced parameter variations and speed reversal conditions will be investigated in future work.

6. CONCLUSION

This study proposes a gain-adaptive super-twisting higher-order sliding mode observer (GAST-HOTSMO) for high-precision sensorless SPMSM control. By utilizing a second-order sliding mode structure and a barrier function-based adaptive law, the proposed scheme eliminates conventional low-pass filters, effectively suppressing chattering and phase lag under dynamic perturbations. Extensive simulations and experiments validate that GAST-HOTSMO significantly reduces harmonic distortion, minimizes position estimation errors, and accelerates transient recovery compared to conventional methods.

Future work will focus on two aspects: 1) extending the adaptive observer framework to mitigate machine parameter variations under extreme operating conditions, and 2) optimizing the estimation performance to further suppress higher-order harmonics in back-EMF components.

ACKNOWLEDGEMENT

This work was supported in part by the Natural Science Research Project of Anhui Educational Committee under Grant No. 2025AHGXZK31006, in part by the Research Foundation of Jiangsu Engineering Research Center for Bionics Control Technology and Equipment under No. FSKZ202503, in part by the Anhui International Joint Research Center for Ancient Architecture Intellisencing and Multi-Dimensional Modeling under Grant No. GJZZX2025KF03, and in part by the Graduate Innovation Fund of Anhui University of Science and Technology under grant No. 2026cx2056.

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