2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)
June 28-30, 2023. Seattle, Washington, USA

Adaptive Extended State Observer-Based Terminal Sliding Mode Control for PMSM System with Uncertainties

Yuxiang Ma, Yunhua Li, *Senior Member, IEEE,* and Tao Qin

***Abstract*—An adaptive extended state observer (AESO)-based terminal sliding mode control (ATSMC) is proposed for PMSM systems with uncertainty in this paper. Firstly, in order to handle various uncertainties explicitly and effectively, to divide the uncertainty into structured uncertainty (i.e., parametric uncertainty) and remaining uncertainty (i.e., external disturbance and unmodeled dynamics) two types is carried out. The former is handled by introducing adaptive parameter estimation (APE), and the latter is considered as lumped disturbance and compensated by extended state observer (ESO). In this way, the cooperation between parameter adaption and disturbance observer is established and the estimation accuracy of ESO is guaranteed under the parameter perturbation. Then, a terminal sliding mode function with fractional order is used to achieve system state finite-time convergence. Thus, a compound nonlinear controller is obtained by integrating different mechanisms. The main advantages of this controller are only the output feedback used, and strong disturbance rejection ability. Experimental results show the efficiency of the proposed method.**

***Index Terms*—motion control, sliding mode control, uncertainty, state observer, parameter estimation.**

I. Introduction

Permanent magnet synchronous motor (PMSM) has many advantages of high efficiency, high power density and high response ability. PMSM has been widely used in industry, such as the industrial robot, computer numerical control machining, electric excavator, vehicles, aerospace, etc. especially in electric vehicles (EV) [1]. Due to the parametric uncertainties and external disturbances, the classical linear controller cannot achieve a satisfactory result. In many related works, various nonlinear control methods have been proposed, such as adaptive control (AC) [2], fuzzy inference [3], sliding mode control (SMC) [4]. SMC has attracted extensive attention because of its robustness and effectiveness. But, it is difficult to reconcile the contradiction between alleviating chattering and improving robustness.

One method is to design a continuous nonlinear function to replace the traditional switching term. In [5], a model-based switching function was designed for a robotic. In [6], a hyperbolic function was used to design a nonlinear reaching law. But the continuous nonlinear terms are complicated, and some nonlinear terms are very sensitive to state changes. The other method is adaptive switching term. In [7], an adaptive switching term was designed, and the switching gain is related to sliding dynamics. In [8], a T-S fuzzy parameter adaptive was designed. In this way, a smooth control action along the sliding surface is achieved. Compared with above two methods, the observer-based SMC is a simpler method in which disturbances are estimated and compensated by the observer. In [9], a compound terminal sliding mode control (TSMC) based on extended state observer (ESO) was proposed, which can alleviate chattering without sacrificing robustness. ESO considers internal uncertainties and external disturbances as lumped disturbance. Obviously, ESO does not consider various uncertainties explicitly and separately. If the true value of observer parameter is far from nominal value, the estimation accuracy of ESO will be seriously reduced. Conventional ESO-based methods cannot achieve satisfactorily in heavy-structured-uncertainty systems, and the estimation accuracy of AC is easily affected by external disturbances.

In addition, classical robust controls require high gain or high-frequency feedback to suppress disturbances for strong robustness. However, high gain will amplify system noise or excite unmodeled dynamics, which is difficult to be directly applied in practice. In addition, classical disturbance observer considers all structured/parameter uncertainties and unstructured uncertainties as lumped disturbance. Those uncertainties are not considered explicitly and separately. This degrades the estimation accuracy of the disturbance observer in heavy-structured-uncertainty systems. In this paper, APE and ESO are incorporated in the robust controller design, such that the unknown parameters are updated and the load disturbance is compensated. The structured/parameter uncertainties are handled by the parameter adaptive mechanism. The remaining uncertainties are compensated by ESO-base disturbance compensation. This makes the estimation accuracy of ESO to be guaranteed under the parameter perturbation. By integrating different mechanisms, their respective limitations are overcome. Compared with traditional TSMC, This method improves the control performance with smaller switching gain. Compared with AC, the robustness is improved. Compared with classical linear ESO (LESO), the interference of parameter uncertainty on disturbance estimation is reduced. Note that TSMC can achieve state convergence in finite-time. The APE mainly contributes to structured uncertainties. The AESO is used to handle unstructured uncertainties. Each method has its unique contribution. So, these different methods can be integrated. The ATSMC is characterized by output feedback only, easy implementation and does not need for accurate parameters.

This work is supported by National Natural Science Foundation of China and Shanxi Coal-based Low Carbon Joint Fund under the grant No. U1910211. (Corresponding author: *Yunhua Li, e-mail:yhli@buaa.edu.cn*.)

Yuxiang.Ma, Yuhua.Li, and Tao Qin are with the School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China.

Therefore, a new mechanism combining parameter adaptation and disturbance observer is proposed to solve above problems. Note that adaptive ESO (AESO) is not a simple combination. A novel AESO-based TSMC (ATSMC) method combining AESO and TSMC is proposed for PMSM systems. The major contributions are:

1) An APE is incorporated into ESO to handle various uncertainties separately. Parameter uncertainties are mainly handled by APE, and other uncertainties are estimated and compensated by ESO so that the cooperation between AC and observer is established.

2) By integrating APE and ESO in the TSMC design, the performance is improved and finite-time convergence is achieved. Specifically, the AESO can help TSMC deal with disturbances and alleviate chattering without sacrificing robustness.

3) A new compound control method by integrating different mechanisms is proposed.

This paper structure is as follows. Section II is modeling and problem formation. In Section III, a compound controller is designed. Closed-loop stability and error dynamics are discussed. In Section IV, the experimental results are presented. Conclusions are shown in Section V.

II. PROBLEM FORMULATION

Here, a speed servo system is considered. For a single speed system can be described as

$$\dot{\omega}(t) = -\frac{B_m}{J}\omega(t) + \frac{K}{J}u - \frac{T_L}{J} \tag{1}$$

where B_m is viscous friction coefficient, ω is rotor velocity (RPM), K is torque constant (N·m/V), T_L is disturbance (N·m), J is moment of inertia (kg•m^2), u is control signal (V). Here, SVPWM was applied and two PI controllers are applied to d and q loops. So, the aim of this work is to design a speed controller to make the system have good performance under various uncertainties. For simple， system (1) is rewritten as

$$\dot{\omega}(t) = -a\omega(t) + bu(t) + d \tag{2}$$

where $a=B_m/J$, $b=K/J$, $d=-T_L/J$. The disturbance d will be transmitted to the motor system. $|d| \le L_1$ and $|\dot{d}| \le L_2$.

III. DESIGN OF CONTROLLER

In this section, to handle various uncertainties explicitly and separately, an AESO is proposed. The main idea is to employ AC to handle structured uncertainties and the remaining unstructured uncertainties are estimated by ESO and compensated by a feedforward channel.

A. APE

For ESO with constant parameters, parameter perturbation will make the ESO output oscillate and worsen the estimation accuracy. To handle the above problem, this paper adopts different mechanisms to deal with uncertainties respectively. System (2) is rewritten as

$$\dot{\omega}(t) = -a\omega(t) + bu(t) + d = \phi\delta + d \tag{3}$$

where $\phi=[-\omega, u]$ is a known regressor vector, $\delta=[a, b]^T$ is unknown parameter to be estimated. The following filtered variables are defined as

$$\begin{cases} k_l\dot{\omega}_f + \omega_f = \omega, \ \omega_f(0) = 0 \\ k_l\dot{\phi}_f + \phi_f = \phi, \quad \phi_f(0) = 0 \end{cases} \tag{4}$$

where ω_f and ϕ_f are the filtered values of ω and ϕ, k_l is a positive constant. The same filter operation is applied to d to get an auxiliary variable d_f (only used to analysis): $k_l\dot{d}_f + d_f = d$, $d_f(0) = 0$. Here, a filtered matrix $M \in R^{2\times2}$ and a filtered vector $N \in R^{2\times1}$ are defined as

$$\begin{cases} \dot{M} = -lM + \phi_f^T\phi_f, & M(0) = 0 \\ \dot{N} = -lN + \phi_f^T[(\omega-\omega_f)/k_l], & N(0) = 0 \end{cases} \tag{5}$$

where l>0 is a design parameter. Integrating both side of (5)

$$\begin{cases} M(t) = \int_0^t e^{-l(t-\tau)}\phi_f^T\phi_f d\tau \\ N(t) = \int_0^t e^{-l(t-\tau)}\phi_f^T[(\omega-\omega_f)/k_l]d\tau \end{cases} \tag{6}$$

Lemma 1([10]): If the vector ϕ is persistently excitation (PE) (e.g., exist $\nu > 0, \gamma > 0$ such that $\int_t^{t+\nu}\phi^T(r)\phi(r)dr > \gamma I$, $\forall t > 0$), the M is positive definite and $\lambda_{\min}(M) > \sigma > 0$.

From (5) and (6), following relationship can be obtained as

$$N = \int_0^t e^{-l(t-\tau)}\phi_f^T(\phi_f\delta + d_f)d\tau = M\delta + \Delta \tag{7}$$

where $\Delta = \int_0^t e^{-l(t-\tau)}\phi_f^T d_f d\tau$. Define the estimation error $\tilde{\delta} = \hat{\delta} - \delta$, $\hat{\delta} = [\hat{a}, \hat{b}]^T$ is the estimation of δ, and an auxiliary variable is defined as

$$W = M\hat{\delta} - N = M\tilde{\delta} - \Delta. \tag{8}$$

Here, an adaptive parameter estimation law about $\hat{\delta}$ is designed as

$$\dot{\hat{\delta}} = -\Gamma M^T W / \|W\| \tag{9}$$

where $\Gamma > 0$ is a constant gain matrix. Thus the adaptive estimation law is driven by the estimation error.

Lemma 2([11]): For a continuous system $\dot{x} = \phi(x,t)$, $\phi(0,t) = 0$, $x \in \mathrm{R}^n$, there is a continuously differentiable positive definite function $V(x,t)$ and real number h_1>0, 0<h2<1, if $\dot{V} \le h_1 V^{h_2}(x,t)$ holds, then function $V(x, t)$ will converges to zero in in finite time where $t \le (1/h_1(1-h_2))V^{1-h_2}(x(t_0),t_0)$ for initial condition $x(t_0)$.

Theorem 1: For system (3) with adaptive law (9) and filtered variables in (4)–(8), if the regressor vector ϕ is PE, then the estimation error $\tilde{\delta} \to 0$ in finite time, and $\tilde{\delta}$ is bounded.

Proof: According to variable (8) we have $M^{-1}W=\tilde{\delta}-M^{-1}\Delta$. Design Lyapunov function as $V_1=0.5W^TM^{-1}M^{-1}W$ and the derivative of V is

$$\begin{aligned}\dot{V}_1&=W^TM^{-1}\frac{\partial M^{-1}W}{\partial t}\\&=W^TM^{-1}(\dot{\tilde{\delta}}-\frac{\partial M^{-1}}{\partial t}\Delta-M^{-1}\frac{\partial\Delta}{\partial t})\\&=W^TM^{-1}(\dot{\tilde{\delta}}-M^{-1}\dot{M}M^{-1}\Delta-M^{-1}\dot{\Delta}).\end{aligned}\tag{10}$$

Define $\bar{\Delta}=-M^{-1}\dot{M}M^{-1}\Delta-M^{-1}\dot{\Delta}$,here $\Delta=\int_0^t e^{-l(t-\tau)}\phi_f^T d_f d\tau$ and $\dot{\Delta}$ are bounded as long as ϕ and d are bounded. According to Lemma 1, the positive definite matrix M satisfies $\lambda_{\min}(M)>\sigma>0$. So M^{-1} is bounded. $\bar{\Delta}$ is bounded for bounded disturbance, i.e., $\|\bar{\Delta}\|\le L_3$. We have

$$\begin{aligned}\dot{V}_1&=W^TM^{-1}\dot{\tilde{\delta}}+W^TM^{-1}\bar{\Delta}\\&=-W^TM^{-1}\Gamma\frac{M^TW}{\|W\|}+W^TM^{-1}\bar{\Delta}\\&\le-(\lambda_{\min}(\Gamma)-\|M^{-1}\bar{\Delta}\|)\|W\|\le-\mu_1\sqrt{V_1}\end{aligned}\tag{11}$$

where

$\mu_1=(\lambda_{\min}(\Gamma)-L_3/\sigma)\sqrt{2/\lambda_{\max}^2(M^{-1})}$, $\|M^{-1}\bar{\Delta}\|\le L_3/\sigma$ is bounded. A suitable Γ can be selected to meet $\lambda_{\min}(\Gamma)>L_3/\sigma$. So $\mu_1>0$. According to Lemma 2, V converges to zero with time t_c

$$t_c\le 2\sqrt{V_1(0)}/\mu_1.\tag{12}$$

When $V\to 0$, $M^{-1}W\to 0$ is achieved in finite tine, i.e., $\lim\tilde{\delta}=M^{-1}\Delta$.

Remark 1: The finite-time convergence and boundedness of the parameter estimation error are achieved. Compared with conventional gradient methods and recursive least square methods, the observer or predictor design is avoided. In [12] and [13], similar APE methods are used to achieve exponential convergence, and the convergence rate is slow.

B. AESO

Unmodeled dynamics, parameter mismatches, and external disturbances will cause perturbation or non-ideal effects. These perturbations can be considered as disturbances. In system (3), $a=a_n+\Delta a$, $b=b_n+\Delta b$, a_n and b_n are nominal values, Δa and Δb are perturbation. Here, an AESO method by integrating APE is proposed. APE is introduced to update unknown parameters. So the speed system can be rewritten as

$$\dot{\omega}=-\hat{a}\omega+\hat{b}u+d\tag{13}$$

Let $z_1=\omega$ and $z_2=d$, then an extended system is obtained

$$\begin{cases}\dot{z}_1=-\hat{a}z_1+\hat{b}u+z_2\\ \dot{z}_2=\dot{d}\end{cases}.\tag{14}$$

So, d is estimated by AESO and the AESO is designed as

$$\begin{cases}\dot{\hat{z}}_1=\hat{z}_2-\hat{a}z_1+\hat{b}u-\alpha_1\omega_0(\hat{z}_1-z_1)\\ \dot{\hat{z}}_2=-\alpha_2\omega_0^2(\hat{z}_1-z_1)\end{cases}\tag{15}$$

where $\hat{z}_1$ and $\hat{z}_2$ are the estimation of z1 and z_2, $\omega_0>0$ is the observer gain, α_1 and α_2 are constant gains.

Remark 2: According to Lemma 1 in [14], the estimated states are always bounded and there exist a constant $\sigma_i>0$ such that $\sigma_i=O(1/\omega_0^\rho)$ for $t\to\infty$, ρ is a positive integer. This means that if the gain ω_0 is large enough, the estimation error will be small enough. But high-gain might amplify the noise effect and lead to instability.

C. Design of Speed Controller

By using the estimated parameters and estimated disturbance from APE and AESO, a TSMC is designed. Define the tracking error as $e=\omega^*-\omega$, where ω^* is reference speed, thus the error state equation is $\dot{e}=\dot{\omega}^*-\hat{a}e+\hat{a}\omega^*-\hat{b}u-d$. If the reference signal ω^* is not a priori, then $\dot{\omega}^*$ is difficult to obtain directly. For convenience, $\dot{\omega}^*$ is considered as disturbance. So

$$\dot{e}=-\hat{a}e-\hat{b}u+\hat{a}\omega^*-d\tag{16}$$

Here, PI-type sliding mode function and reaching law are designed as

$$\begin{cases}s=c_1e+c_2\int_0^t|e|^\alpha\operatorname{sign}(e)d\tau\\ \dot{s}=-ks-\varepsilon\operatorname{sign}(s)\end{cases}\tag{17}$$

where $\dot{s}=c_1\dot{e}+c_2|e|^\alpha\operatorname{sign}(e)=-ks-\varepsilon\operatorname{sign}(s)$, $c_1>0$, $c_2>0$, $0<\alpha<1$. Then, substituting (13) into $\dot{s}$ and consider the estimated disturbance, the ATSMC can be designed as

$$u=(-c_1\hat{a}e+c_1\hat{a}\omega^*-c_1\hat{z}_2+c_2|e|^\alpha\operatorname{sign}(e)+ks+\varepsilon\operatorname{sign}(s))/c_1\hat{b}\tag{18}$$

where $\varepsilon>0$, d is replaced by $\hat{z}_2$ due to disturbance compensate. Finally, the entire control system is shown in Fig. 1.

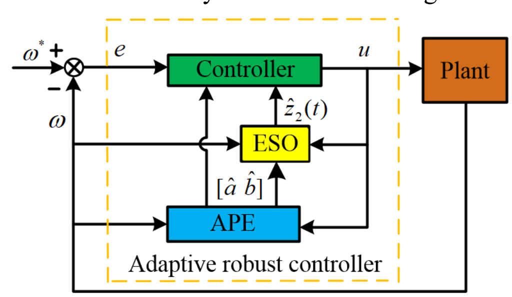

Fig. 1. Diagram of the proposed ATSMC.

Remark 3: The aim of ATSMC proposed in this paper is to combine adaptive technology and observer-based control method to handle various uncertainties explicitly and separately and improve the performance of motion system. ATSMC improves the closed-loop performance compared with conventional TSMC and LESO. Note that compound control methods can deal with more complex objects. That is why compound control methods have received more and more attention. The ATSMC proposed in this paper can be considered as a compound control method. Moreover, this control scheme realizes the cooperation of various methods rather than simple addition.

D. Tuning Guidelines

For APE, the constant k_l is a sufficiently small value which represents the bandwidth of filter. Constant l can be considered as a forgetting factor, $0<l<1$. Gain Γ can improve estimation performance and convergence speed, but may excite parameter oscillations.

For the ESO, The ω0 can be set as the sampling frequency. In general, ω_0=sampling frequency is too large. Then gradually decrease ω_0 until the estimated value is stable.

For the control law, only $c_1\hat{a}\omega^*$ is considered first. The term $c_1\hat{a}\omega^*$ can be considered as an open-loop proportional control. Gradually increase c_1 to make the output track the reference. Here, c_1 is selected as 1. Then gradually increase k to reduce the steady-state error. Finally, gradually increase c_2 to speed up the convergence.

IV. Simulations and Experiments

A. Simulation Results

Simulations are carried out to demonstrate the effectiveness of proposed ATSMC. Simulations are implemented in Matlab/Simulink. The plant is

$$\dot{x}=-a(t)x+b(t)u(t)-d(t) \tag{19}$$

where $a(t)$ and $b(t)$ are time-varying parameters from 0.1 to 0.2 and 45 to 60, respectively. External disturbance $d(t)$ changes from 3 to 6 when t=3. AESO is designed as (15), APE is designed as (4)–(9). The speed control law is designed as (18). Parameters are as follows: c_1=1, c_2=0.1, k=2, α=5/9, l=1, k_l=0.001, Γ=[0.015, 10], ω_0=300, α_1=3, α_2=1, the initial condition is $\hat{\delta}=[1,10]$, reference speed is ω^*=600sin(0.4πt), sample time is 1ms. Simulation results are shown in Fig. 2.

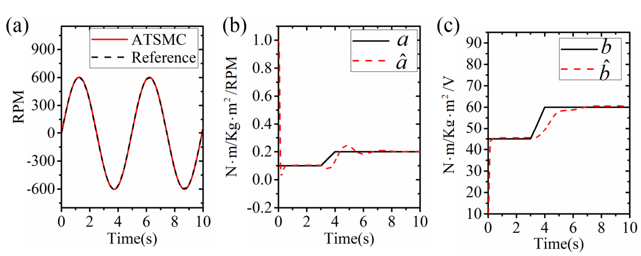

Fig. 2. (a) Speed curve. (b) Estimated parameter a. (c) estimated parameter.

In Fig. 2(a), the reference speed is well tracked. This shows that ATSMC still maintains excellent performance under time-varying parameters and external disturbance. In Fig. 2(b) and (c), time-varying parameters can still be estimated by APE under time-varying disturbance $d(t)$.

Here classical LESO and AESO are compared. The classical LESO is designed as

$$\begin{cases}\dot{\hat{z}}_1=\hat{z}_2-a_n z_1+b_n u-\alpha_1\omega_0(\hat{z}_1-z_1)\\ \dot{\hat{z}}_2=-\alpha_2\omega_0^2(\hat{z}_1-z_1)\end{cases}$$

where a_n=0.1 and b_n=45 are constant nominal parameters. So parameter perturbations are not considered in classical LESO. AESO is designed as (12) where parameters are updated by APE. In Fig. 3(a), Classical LESO can provide a good estimate of d(t) if the parameters are accurate. However, the estimation accuracy deteriorates when the parameters change. For the AESO, parameters can still be well estimated by AESO after parameter changes.

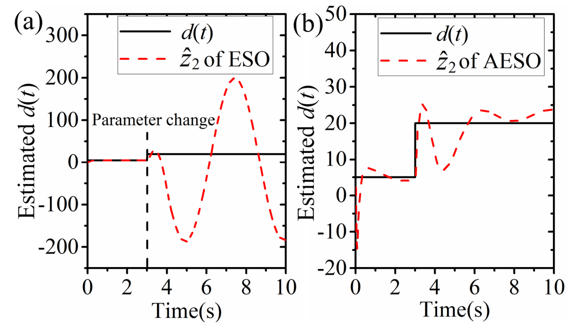

Fig. 3. Classic LESO vs AESO. (a) $d(t)$ estimated by classical LESO. (b) $d(t)$ estimated by AESO.

B. Experiment System

In this section, experiments are carried out on a servo drive setup. To demonstrate the improvement of the proposed method, ATSMC is compared with LESO-based TSMC (LTSMC) and uncompensated TSMC. The experimental setup is shown in Fig. 4. Two PMSMs (model 190N6K52-20MN1) are connected, one motor as driving motor and the other as load motor. The rated rotational speed is 2000rpm, rate torque is 31N•m, torque constant K=3.1N•m/V, moment of inertia J=0.069kg•m2, B_m=0.003N•m/rpm, and rate power is 6.5kW.

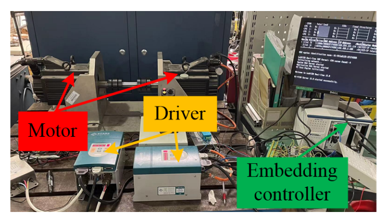

Fig. 4. Membership function curves of e, ec, $k_{\Delta p}$, $k_{\Delta I}$, $k_{\Delta D}$

Compare ATSMC with conventional TSMC and LTSMC to demonstrate its performance. The parameters of controller are given in Table I.

TABLE I
PARAMETERS OF CONTROLLER

a_n	0.04	b_n	45	α	5/9
c_1	1	c_2	0.2	k	2.5

The controllers in experiments are as follows:

1) Conventional TSMC: Sliding function and reaching law are defined in (17). We have $\dot{s}=c_1\dot{e}+c_2|e|^\alpha\operatorname{sign}(e)=-ks-\varepsilon\operatorname{sign}(s)$, substituting (16) into $\dot{s}$ yields $u=(-0.04e+0.04\omega^*+0.1|e|^\alpha\operatorname{sign}(e)+2.5s+7\operatorname{sign}(s))/45$.

2) LTSMC: Here LESO is introduced. So the disturbance d is estimated and compensated by LESO. Therefore the LTSMC is $u=(-0.04e+0.04\omega^*-\hat{z}_2+0.1|e|^\alpha \text{sign}(e)+2.5s+7\text{sign}(s))/45$ where $\hat{z}_2$ is compensation term.

3) ATSMC:

$u=(-\hat{a}e+\hat{a}\omega^*-\hat{z}_2+0.1|e|^\alpha \text{sign}(e)+2.5s+7\text{sign}(s))/\hat{b}$. For APE, k_l=0.005, l=0.9, $\Gamma=diag[0.2\ \ 20]$.

C. Experiment Results

Here, the tracking performances under three controllers are tested. A time-varying reference signal ω^*=600sin(0.4πt) is given to test the tracking performance. A torque (6N•m) is loaded. For comparison, Root Mean Squared Error (RMSE) and Maximun Tracking Error (MTE) are defined as follows:

$$\begin{cases} \text{RMSE}=\sqrt{(\sum_{k=i}^{i+N} e^2(k))/N} \\ \text{MTE}=\max|e(k)| \end{cases} \quad (20)$$

The speed curves are shown in Fig. 5. The ATSMC gives the best results. The start performance is better, and the overshoot is smaller. Especially in the top area of the sinusoidal signal, ATSMC also shows good tracking accuracy.

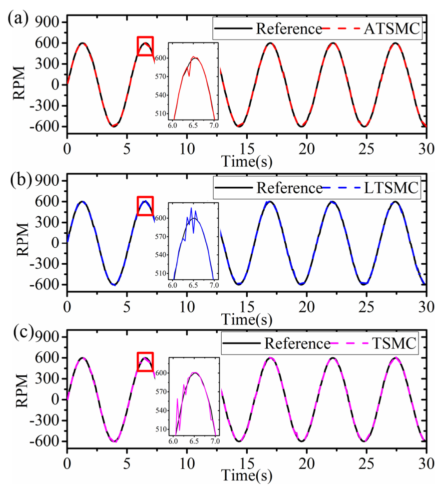

Fig. 5. Speed curves. (a) ATSMC. (b) LTSMC. (c) TSMC.

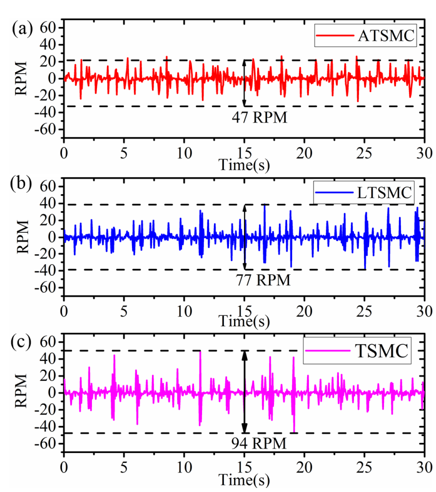

Fig. 6. Tracking errors. (a) ATSMC. (b) LTSMC. (c) TSMC.

The error curves are shown in Fig. 6. The ATSMC gives the best results. In Fig.6, ATSMC is closer to the reference signal than other controllers, which shows that ATSMC has a better tracking performance for time-varying signal. The tracking errors of three controllers are 47RPM, 77RPM, and 94RPM. The tracking error of ATSMC is reduced by 39% and 50% compared with LTSMC and TSMC, respectively. The error of LTSMC is reduced by 18% compared with TSMC. This is because ESO-based disturbance compensation enhances robustness. Experiments show that the observer-based disturbance compensation technology is an effective method to enhance robustness and improve system performance. Observer technology has been combined with various control methods. The observer can be designed as an independent unit to simplify the design difficulty. Therefore, a compound controller combining various advanced methods is proposed.

Fig. 7 depicts the results of the parameter estimation. As shown in Fig. 7(a) and (b), the proposed APE can guarantee the convergence of parameter estimation. In particular, the parameter $\hat{a}$ related to friction coefficient varies along with speed ω, and the control gain $\hat{b}$ only slightly oscillates. In Fig. 8, the disturbance estimation of AESO fluctuates less. The curve of AESO is smoother than that of LESO.

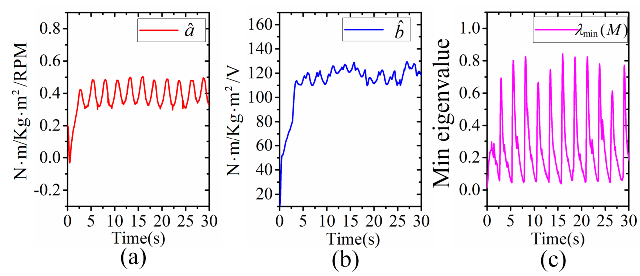

Fig. 7. Parameter estimation and excitation level. (a) $\hat{a}$. (b) $\hat{b}$. (c) Excitation level $\lambda_{\min}(M)$.

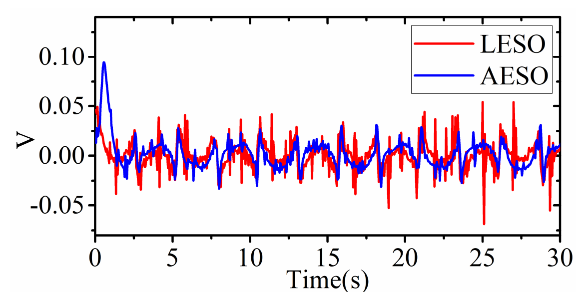

Fig. 8. Disturbance estimation results of LESO and AESO

Moreover, in this case, estimated parameters are time-varying, which often happens in practice. Obviously, AESO can provide accurate disturbance estimation, and the estimated signal is smoother. This can not only improve the control performance but also reduce the control chattering caused by signal oscillation. The good performance of the closed-loop system is still guaranteed. This shows that the system is robust to uncertainties.

V. CONCLUSION

To effectively deal with various uncertainties in the PMSM systems, a compound control method is proposed. Compared with traditional ESO-based methods, the proposed compound ATSMC improve the lumped disturbance estimation performance under parameter perturbation. The lumped disturbance is compensation by an observer-based feedforward channel and the unknown parameters in observer and controller are updated by parameter estimation. At the same time, by the active disturbance compensation based on AESO, sliding mode chattering can be significantly decreased without sacrificing robustness. Since the proposed ATSMC does not require accurate parameters and is only based on output feedback. So it is easier to implement in practice. All experiment results verify that the proposed ATSMC scheme can effectively deal with parameter uncertainties, external disturbance, and complicated nonlinearities.

REFERENCES

[1] H. J. Raherimihaja, Q. Zhang, Integration of battery charging process for EVs into segmented three-phase motor drive with V2G-mode capability, *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 2834-2844, 2021

[2] D. Xuan. Ba, H. Yeom, J. Kim, Gain-adaptive robust backstepping position control of a BLDC motor system, *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 5, pp. 2470-2481, 2018

[3] S. Chen, H. Chiang, T. Liu, Precision motion control of permanent magnet linear synchronous motors using adaptive fuzzy fractional-order sliding-mode control, *IEEE/ASME Trans. Mechatronics*, vol. 24, no. 2, pp. 741-752, 2019.

[4] V. Repecho, J. Waqar, D. Biel, Zero speed sensorless scheme for PMSM under decoupled sliding mode control, *IEEE Trans. Ind. Electron.*, doi: 10.1109/TIE.2021.3062260.

[5] C. Fallaha, M. Saad, J. Ghommam, Sliding mode control with model-based switching functions applied on a 7-DOF exoskeleton arm. *IEEE/ASME Trans. Mechatronics*, vol. 26, no. 4, pp. 539-550, 2021.

[6] S. Wang, L. Tao, Q. Chen, J. Na, and X. Ren, USDE-based sliding mode control for servo mechanisms with unknown system dynamics, *IEEE/ASME Trans. Mechatronics*, vol. 25, no. 2, pp. 1056-1066, 2020.

[7] G. Kim, K. Hong, Adaptive sliding-mode control of an offshore container crane with unknown disturbances. *IEEE/ASME Trans. Mechatronics*, vol. 24, no. 6, pp. 2850-2861, 2019.

[8] L. Teng, M. A. Gull, and S. Bai, PD-based fuzzy sliding control of a wheelchair exoskeleton robot. *IEEE/ASME Trans. Mechatronics,* vol. 25, no. 5, pp. 2546-2555, 2020.

[9] Y. Ma, D. Li, Y. Li, A novel discrete compound integral terminal sliding mode control with disturbance compensation for PMSM speed system, *IEEE/ASME Trans. Mechatronics*, vol. 27, no. 1, pp. 549-560, 2022.

[10] S. Wang, J. Na, and Y. Xing, Adaptive optimal parameter estimation and control of servo mechanisms: theory and experiments, *IEEE Trans. Ind. Electron.*, vol. 68, no. 1, pp. 598-608, 2021.

[11] J. Yang, J. Na, Y. Guo, and X. Wu, Adaptive estimation of road gradient and vehicle parameters for vehicular systems, *IET Control Theory & Applications*, vol. 9, no. 6, pp. 935-943, 2015.

[12] J. Na, Y. Xing, R. Costa-Castell, Adaptive estimation of time-varying parameters with application to roto-magnet plant, *IEEE Trans. System, Man, and Cybernetics: Systems*, vol. 51, no. 2, pp. 731-741, 2021.

[13] S. Wang, J. Na, and Y. Xing, Adaptive optimal parameter estimation and control of servo mechanisms: theory and experiments, *IEEE Trans. Ind. Electron.,* vol. 68, no. 1, pp. 598-608, 2021.

[14] Y. Yao, Z. Jiao, and D. Ma, Adaptive robust control of DC motors with extended state observer, *IEEE Trans. Ind. Electron.*, vol. 61, no. 7, pp. 3630-3637, 2014.