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Research on Permanent Magnet Synchronous Motor Control System Based on Adaptive Kalman Filter

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Abstract: A sensorless control system of a permanent magnet synchronous motor based on an extended Kalman filter (EKF) algorithm faces problems with inaccurate or mismatched process noise statistics. This problem affects the performance of the filter, resulting in an inaccurate estimation of motor speed. To address the above problem, this paper proposes a parameter-adaptive Kalman filter algorithm that does not depend on precise noise system covariance. This method can significantly reduce the negative impact of the noise statistical mismatch on motor speed estimation. In addition, the method uses adaptive covariance prediction and removes the original covariance checks in the EKF, thus reducing the calculation burden. The simulation results show that, compared with the traditional EKF algorithm, the algorithm proposed in this article can effectively reduce the steady-state jitter and improve the filtering adaptability and calculation accuracy.

Keywords: extended Kalman filter; parameter adaptive extended Kalman filter; parameter adaptive extended Kalman filter; sensorless control

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1. Introduction

In recent years, the development and availability of permanent magnet materials have made permanent magnet synchronous motors (PMSMs) develop rapidly. Moreover, PMSMs have the advantages of small volume, high efficiency, high power density, and wide speed range [1–3]. Thanks to the application of advanced methods such as vector control and space vector pulse width modulation, PMSMs can realize higher performance speed and position control in the digital control system. In this way, the application of high-performance shifting motors can become widespread. At present, PMSMs are widely used in new energy vehicles, CNC machine tools, and robots, and has a good development prospect [4,5].

To make the whole PMSM control system operate stably, the motor needs to get the position and speed of the rotor in real-time [6]. To detect the rotor position information, the universal solution is to install mechanical position sensors, such as photoelectric encoders, rotary transformers, etc. However, the mechanical sensor has several disadvantages [7,8]. Firstly, the mechanical position sensor increases system cost and circuit size, limiting the promotion application of products. Secondly, mechanical sensors are susceptible to noise, and the operating temperature range is limited, reducing the system's operational reliability [9]. Thus, installing mechanical position sensors is not an optimal way to obtain the position and speed of the rotor in real time.

Due to the limitations of the mechanical sensors, a number of studies use various non-sensor techniques to estimate speed and location. They can be divided into active methods and passive methods: the first is to inject high-frequency signals using rotor anisotropy [10,11], and the second is based on observer [12]. For example, the authors in [13] developed the model reference adaptation method that used adaptive parameter identification theory for sensorless control of PMSMs. The method consists of an adjustable model, reference model, and adaptive law, according to the error of the current state variable adaptive adjustment adjustable model parameter. This method can keep the output of the reference model consistent with the adjustable model. Authors in [14,15] developed a sliding model observer method. This method performed closed-loop correction and adjustment on the observed current to be consistent with the actual current. The control function then output the back EMF through a low-pass filter and obtained the position angle error through arctangent. Authors in [16,17] developed the EKF-based approach, which performed an online estimation of the system state to implement online control. Among the above methods, the model reference adaptive method is susceptible to stator resistance variation during the operation process [18]. The sliding mode observer has a discontinuous switch function, which will produce large jitter and noise. The EKF can suppress noise while overcoming other algorithm defects and is easy to implement in discrete time domains. Therefore, the EKF algorithm is widely used to estimate the speed and position of PMSMs [19]. Authors in [9,20] proposed a speed estimation method using the EKF algorithm, and achieved the closed-loop speed control system of PMSMs, which proved that the EKF algorithm is feasible for PMSM closed-loop control.

The EKF algorithm considers the impact of system and measurement noise, providing a random method for status and parameter estimation. However, the EKF algorithm requires complete dynamic model parameters and statistical model parameters to achieve optimal performance, which is the accurate known system process noise covariance. In practical applications, the process noise covariance uncertainty and inaccuracy will lead to the deviation of the filter and seriously affect the filter's performance. Therefore, research on the filtering problem of inaccurate or mismatched system noise covariance is essential [21]. Authors in [22] gave the definition and selection method of EKF parameters, and proposed a parameter adaptive law for speed estimation of PMSM by using the hyperbolic tangent function. Authors in [23] proposed a new noise model identification method for the sensorless control system, which optimized the acquisition of covariance matrix in EKF based on the ant colony algorithm. The above-mentioned methods both depend on the accurate selection of process noise parameters, which needs many experiments to obtain an excellent value and increases more workload in application [24,25].

To address the above problems, this paper proposes a new linear time-invariant parameter adaptive Kalman Filter (PAEKF) for the PMSM control system. The main innovation of this method is that the priori error covariance is adjusted on-line by feedback mining of a posteriori variance instead of using traditional method to estimate the process noise covariance. This new adaptive Kalman filter has multiple advantages. Firstly, the filtering performance of PAEKF does not depend on the accurate process noise covariance. Compared with the EKF, the proposed method reduces the work of obtaining the optimal noise parameters. Secondly, the amount of calculation required by PAEKF is equivalent to the EKF. Finally, the stability and accuracy of PAEKF in velocity estimation are better than the EKF. The remainder of this paper is organized as follows. In Section 2, the PAEKF algorithm is proposed, and the mathematical model of PMSM under EKF and PAEKF algorithm is given. In Section 3, the PAEKF algorithm proposed in this article is compared with EKF and existing adaptive methods, respectively. The proposed method is applied to practice to verify effectiveness. Finally, in Section 4, the research contents are summarized and the future work plan is given.

2. Theoretical Analysis of the EKF

This chapter will give the mathematical model of PMSM. The mathematical model is linearized and discretized to apply to EKF and PAEKF.

2.1. The EKF Model of the PMSM

The mathematical model of PMSM in the αβ coordinate system is as follows (1). The model is a prerequisite for the application of EKF:

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

where $\begin{bmatrix} u_\alpha & u_\beta \end{bmatrix}^T$ and $\begin{bmatrix} i_\alpha & i_\beta \end{bmatrix}^T$ are stator voltage and the stator current, respectively, R_s is the stator resistance, L_s is the PMSM winding inductance, ψ_f is the rotor permanent magnet flux.

Based on (1), the speed is assumed to be constant in a short sampling time. In the α-β coordinate system, the PMSM equation can be expressed as:

$$\begin{array}{l} \frac{di_\alpha}{dt} = -\frac{R_s}{L_s} i_\alpha + \frac{\psi_f \omega_e}{L_s} \sin\theta + \frac{u_\alpha}{L_s} \\ \frac{di_\beta}{dt} = -\frac{R_s}{L_s} i_\beta - \frac{\psi_f \omega_e}{L_s} \cos\theta + \frac{u_\beta}{L_s} \\ \frac{d\omega_e}{dt} = 0 \\ \frac{d\theta}{dt} = \omega_e \end{array} \quad (2)$$

where $x = \begin{bmatrix} i_\alpha & i_\beta & \omega_e & \theta \end{bmatrix}^T$ is a state variable, $u = \begin{bmatrix} u_\alpha & u_\beta \end{bmatrix}^T$ is a control matrix, $y = \begin{bmatrix} i_\alpha & i_\beta \end{bmatrix}^T$ is an output variable. So Equation (2) can be expressed as the nonlinear state equation of PMSM:

$$\begin{array}{l} \dot{x}(t) = f[x(t)] + B \cdot u(t) + \omega(t) \\ \dot{y}(t) = h[x(t)] + \nu(t) \end{array} \quad (3)$$

where B is the input matrix, $w(t)$ is the state noise, $\nu(t)$ is the measurement noise. Based on the comparison of Formula (2) and Equation (3), the coefficient equation in (4) can be obtained:

$$\begin{array}{l} f[x(t)] = \begin{bmatrix} -\frac{R_s}{L_s} i_\alpha + \frac{\psi_f \omega_e}{L_s} \sin\theta \\ -\frac{R_s}{L_s} i_\beta - \frac{\psi_f \omega_e}{L_s} \cos\theta \\ 0 \\ \omega_e \end{bmatrix}, \\ B = \begin{bmatrix} \frac{1}{L_s} & 0 \\ 0 & \frac{1}{L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \\ h[x(t)] = \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} \end{array} \quad (4)$$

Since PMSM is a continuous nonlinear system, the continuous nonlinear system of the EKF model should be linearized and discretized. The nonlinear Equation (3) can be expressed in the linearization by using the Taylor-level number:

$$\begin{array}{l} \dot{x} = F[x]x + B \cdot u + \omega, \\ \dot{y} = H[x]x + \nu \end{array} \quad (5)$$

The Jacobian matrices $F(x)$ and $H(x)$ can be expressed as:

$$F(x) = \left. \frac{\partial f}{\partial x} \right|_{x=x(t)} = \begin{bmatrix} -\frac{R_s}{L_s} & 0 & \frac{\psi_f}{L_s} \sin\theta & \frac{\psi_f}{L_s} \omega_e \cos\theta \\ 0 & -\frac{R_s}{L_s} & -\frac{\psi_f}{L_s} \cos\theta & \frac{\psi_f}{L_s} \omega_e \sin\theta \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (6)$$

$$H(x) = \frac{\partial h}{\partial x} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{7}$$

The sampling time is assumed to be T, the linear state equation of PMSM can be expressed in the discrete equation:

$$\begin{aligned} x_k &= \Phi x_{k-1} + BTu_{k-1} + \omega_{k-1}, \\ y_k &= Hx_k + \nu_k \end{aligned} \tag{8}$$

where Φ is the state transition matrix of the system, and $\Phi = e^{FT} \approx I + FT$.

The EKF equations of PMSM consist of prediction Equation (9) and correction Equation (10), which can be obtained based on the Kalman filter equations:

$$\begin{aligned} \hat{x}_{k|k-1} &= \hat{x}_{k-1} + [f(\hat{x}_{k-1}) + Bu_{k-1}]T, \\ P_{k|k-1} &= \Phi P_{k-1} \Phi^T + Q. \end{aligned} \tag{9}$$

$$\begin{aligned} K_k &= P_{k|k-1} H^T [H P_{k|k-1} H^T + R]^{-1}, \\ \hat{x}_k &= \hat{x}_{k|k-1} + K_k (y - H\hat{x}_{k|k-1}), \\ P_k &= (I - K_k H) P_{k|k-1} \end{aligned} \tag{10}$$

where $\hat{x}_{k|k-1}$ is a priori estimate at the time k, $P_{k|k-1}$ is a priori estimation covariance matrix, Q is the state noise covariance matrix, K_k is the Kalman gain matrix, R is the measurement noise covariance matrix, $\hat{x}_k$ is the optimal estimate at time k, P_k is the optimal estimated covariance matrix.

According to the EKF model of PMSM, the EKF observer can divide into two steps. The first is the prediction link corresponding to Equation (9). According to the optimal estimation value of the state variable obtained at time $k-1$, the system state variable at the current time is estimated a priori. The prior estimation value $\hat{x}_{k|k-1}$ of the system state variable can be obtained. Then, the covariance matrix $P_{k|k-1}$ of a priori estimation is calculated to obtain the Kalman gain matrix. The second is to update the state variable, which corresponds to Equation (10). The observation error and the minimum variance principle are used to modify the prior estimate of the prediction process. Then the optimal estimate value $\hat{x}_k$ and the optimal estimate variance matrix P_k of the state variable are obtained. However, the speed estimation of the control system based on the PMSM mathematical model requires accurate EKF parameters.

2.2. The PAEKF Model of the PMSM

When the EKF cannot obtain the accurate process noise Q in advance, calculating the prior estimation of covariance in the EKF cannot be used. Using inaccurate or false process noise Q will deviate the priori covariance and Kalman gain matrix. The optimal estimation of Kalman cannot be obtained, which results in instability of the filter. Finally, the accuracy of a priori state estimation is affected. In order to eliminate the dependence of EKF on a priori and exact Q and keep the simplicity of EKF, this paper proposes a new PAEKF to improve the covariance calculation steps of EKF innovatively.

In the model of the PMSM, PAEKF retains the state prediction step, the gain calculation step, and the state update step. The new calculation method replaces the previous covariance calculation step, which can be expressed as [26]:

$$\begin{aligned} P_{k|k-1} &= P_{k-1|k-2} + \Delta P_{k-1}, \\ \Delta P_{k-1} &= (\Delta x_{k-1} \Delta_{k-1}^T - K_{k-1} H P_{k-1|k-2}) / (k-1) \end{aligned} \tag{11}$$

where $P_{k|k-1}$ calculated by the new adaptive Kalman filter method, which represents the estimation of a priori error covariance at time k, ΔP_{k-1} represents the adjustment amount of $P_{k|k-1}$ at the previous time, which can be calculated from a piece of posterior information, Δx_k represents the sequence of a posterior residual vector, which is obtained by the difference between the posterior state vector and the a priori state vector of the Kalman filter, and its representation is

$$\Delta x_k = \hat{x}_k - \hat{x}_{k|k-1}, k = 1, 2, \ldots, k-1 \tag{12}$$

(11) can be obtained by calculating maximum likelihood estimation [26]. Given that Gaussian noise innovation sequence with a mean value of 0 is set up as $e_k = y_k - H\hat{x}_{k|k-1}$. And its covariance is $E(e_k e_k^T) = C_k = HP_{k|k-1}H^T + R$. $\varepsilon_k = \{e_1, e_2, \ldots e_{k-1}\}$ is the set of historical innovation sequence before time k. It is assumed that at any time j ($j = 1, 2, \ldots, k-1$), the priori error covariance of the optimal Kalman filter is invariant. By calculating the maximum likelihood function:

$$L(\hat{P}_{k|k-1}) = \ln P(\varepsilon_k|\hat{P}_{k|k-1}) = \ln \prod_{j=1}^{k-1} P(e_j|\hat{P}_{k|k-1}) = \sum_{j=1}^{k-1} \ln P\left(e_j \middle| \hat{P}_{k|k-1}\right), \tag{13}$$

a priori-error covariance calculation method that does not require noise parameter Q participation is obtained.

Finally, the new adaptive Kalman filter model of permanent magnet synchronous motor can be expressed as

$$\hat{x}_{k|k-1} = \hat{x}_{k-1} + [f(\hat{x}_{k-1}) + Bu_{k-1}]T, \tag{14}$$

$$\begin{aligned} \Delta P_{k-1} &= (\Delta x_{k-1}\Delta_{k-1}^{\mathrm{T}} - K_{k-1}HP_{k-1|k-2})/(k-1), \\ P_{k|k-1} &= P_{k-1|k-2} + \Delta P_{k-1}, \end{aligned} \tag{15}$$

$$K_k = P_{k|k-1}H^T[HP_{k|k-1}H^T + R]^{-1} \tag{16}$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(y - H\hat{x}_{k|k-1}) \tag{17}$$

The new PAEKF model of PMSM is shown in Figure 1. The key of the proposed adaptive Kalman filter is the covariance, which is obtained by using the new adaptive scheme Equation (15). Firstly, the feedback item ΔP_{k-1} can be calculated by the posteriori residual vector sequence Δx_{k-1}. Then, the priori error covariance $\Delta P_{k-1|k-2}$ can be corrected by the feedback term ΔP_{k-1} at the previous time. Finally, the priori error covariance $P_{k|k-1}$ at the new time is obtained.

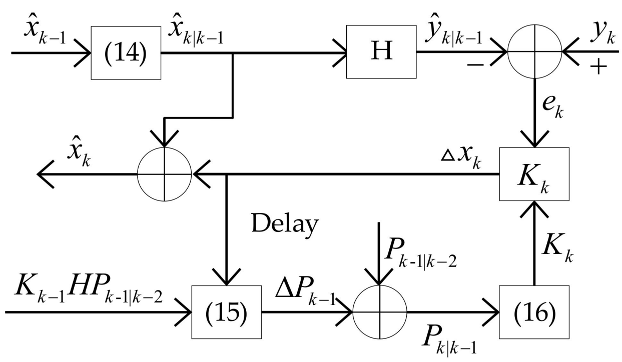


Figure 1. Calculation block diagram of new PAEKF.

2.3. Practical Implementation Considerations

It is impractical to utilize Kalman theory to find the optimal estimation when the Q value is unknown or inaccurate. An appropriate approximation should be close to the optimal infinitely to solve this problem.

When the assumption $P_{k|k-1}$ is a constant, the additive white Gaussian noise e_k is used to estimate the priori error covariance [26]. In actual implementation, to increase this approximate quality, the EKF is used to help filter to realize the rough convergence. Then the new method is implemented. The expression of rough convergence means that it is impossible to estimate the optimal filter with a rough Q value. Therefore, the relatively stable or roughly stable state can be a suboptimal scheme.

3. Simulation Results and Discussions

3.1. Simulation of PMSM Control System Based on EKF and PAEKF

In this section, the simulation model of PMSM is established in MATLAB/Simulink software. The PMSM speed control and estimation block are shown in Figure 2. The performance of the PMSM control system is verified based on PAEKF. With the same measurement covariance matrix, the different noise covariance matrix Q is taken for the PAEKF algorithm and EKF algorithm, respectively. The results show that PAEKF does not need to rely on accurate noise covariance.

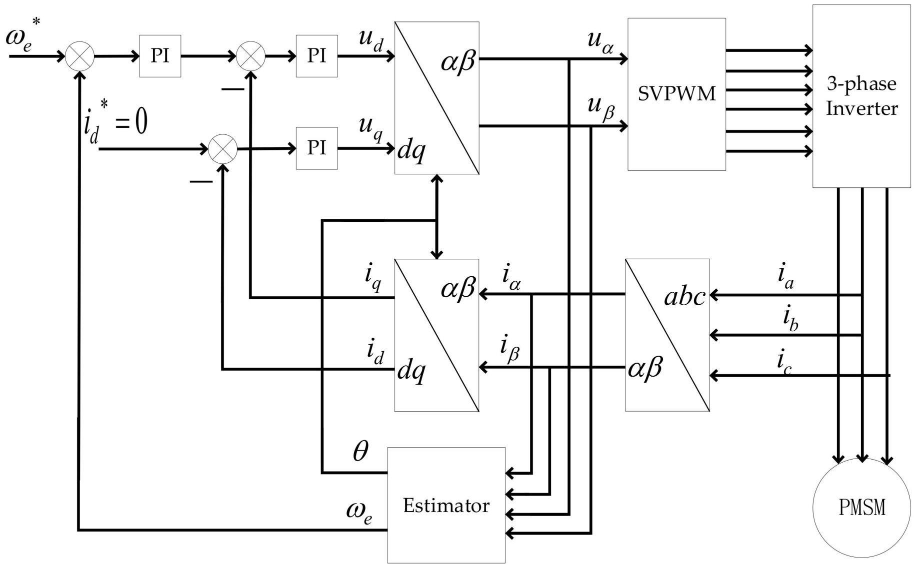


Figure 2. The PMSM speed control and estimation block.

Table 1 shows the relevant parameters of the motor. Table 2 shows different noise covariance matrices Q. It assumes that the measurement noise matrix is diagonal matrix R = diag(0.2,0.2). The PMSM control system is simulated with different noise covariance matrix Q to obtain the speed estimation of PAEKF and EKF. The stability of the estimated speed convergence and the error between the estimated speed and the actual speed is analyzed.

Table 1. PMSM parameters.

Parameter	Values
Voltage V_{dc}(V)	24
Rated speed (r/min)	3000
Inductance L (mH)	1.4
Resistance R (Ω)	0.6
viscous damping F (N·m·s)	1×10^{-4}
Pole pairs p	1
Rotor moment of inertia J (kg·m^2)	1.1×10^{-5}

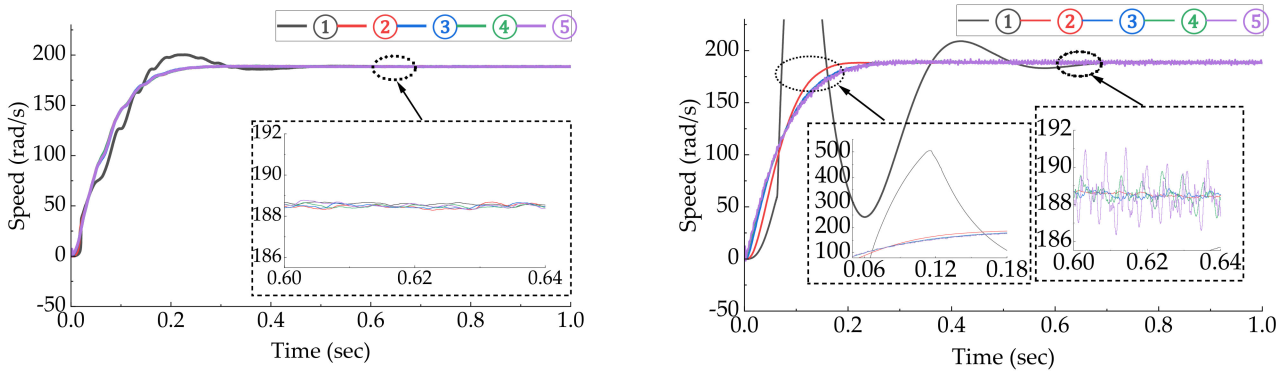
Table 2. Noise covariance Q value.

Numbers	Values
①	Q = diag(0.1,0.1,0.1,0.1)
②	Q = diag(0.1,0.1,0.5,0.1)
③	Q = diag(0.1,0.1,5.0,0.1)

Table 2. *Cont.*

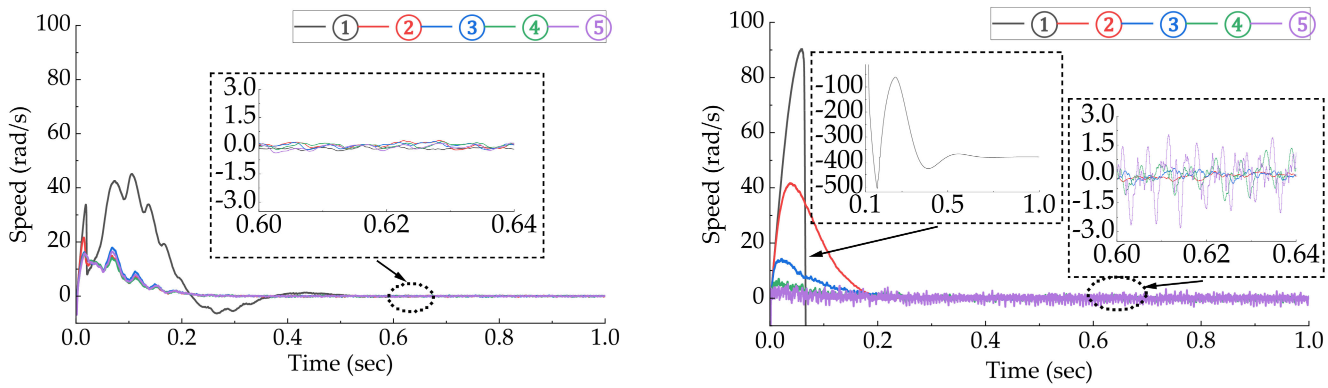
Numbers	Values
④	Q = diag(0.1,0.1,50,0.1)
⑤	Q = diag(0.1,0.1,500,0.1)
⑥	Q = diag(0.1,0.1,0.5,1.0)
⑦	Q = diag(0.1,0.1,5.0,1.0)
⑧	Q = diag(0.1,0.1,50,1.0)
⑨	Q = diag(0.1,0.1,500,1.0)

Figure 3 shows the estimated speed obtained by the PAEKF algorithm and the EKF algorithm with a noise covariance Q of ①–⑤. Figure 4 shows the difference between the estimated speed and the actual speed shown in Figure 3. As shown in Figure 3a, when the Q value is ①–⑤, the estimation speed based on the PAEKF algorithm can converge. Figure 4a shows that the difference between the estimated speed and the actual speed is stable within plus or minus 0.5. When the Q value of the EKF algorithm is ①, the estimated rotational speed can converge in Figure 3b. However, Figure 4b shows that the convergence speed is quite different from the actual speed. Moreover, Figure 4b shows that with the increase in Q value, the estimated speed of the EKF algorithm fluctuates wildly during convergence, and the stability and accuracy are not as good as the PAEKF in Figure 4a.



(**a**) (**b**)

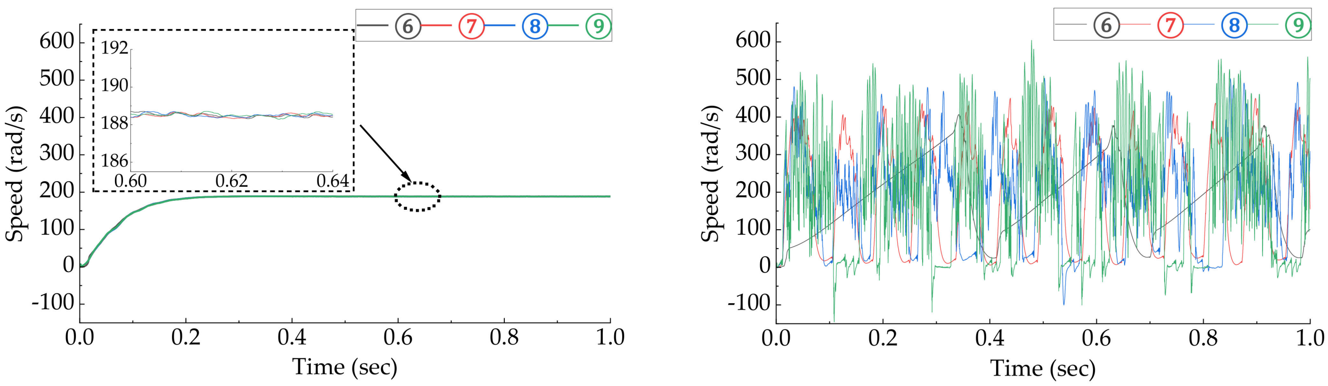
Figure 3. (**a**) When the Q value is ①–⑤, the speed is estimated by the PAEKF. (**b**) When the Q value is ①–⑤, the speed is estimated by the EKF.



(**a**) (**b**)

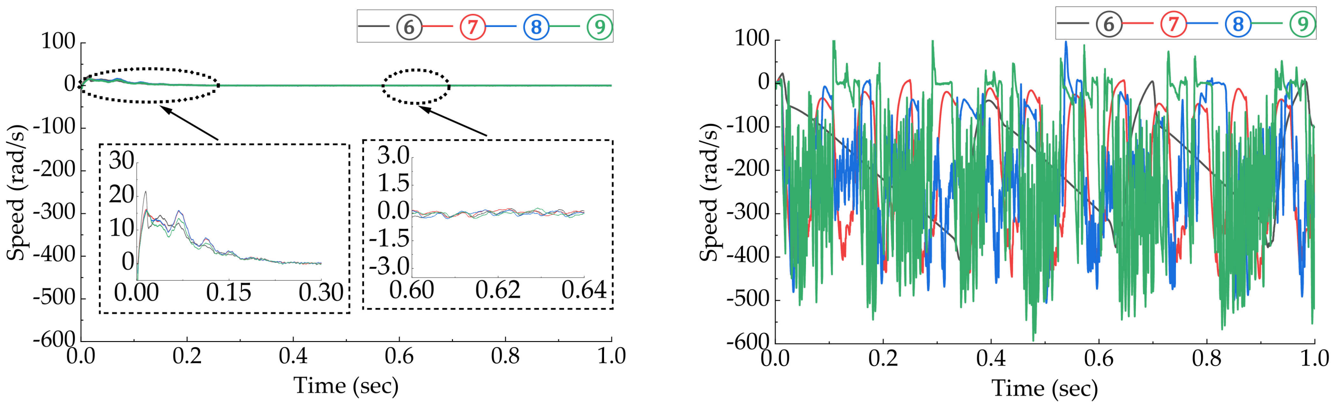
Figure 4. (**a**) When the Q value is ①–⑤, the difference between actual speed and estimated speed based on PAEKF. (**b**) When the Q value is ①–⑤, the difference between actual speed and estimated speed based on EKF.

From Figure 5, under the condition of the noise covariance Q is ⑥–⑨, the estimation speed based on the PAEKF algorithm can converge, and the EKF algorithm cannot converge. The results show that the noise covariance parameter affects the stability of EKF. Figure 6 shows the difference between the actual speed and the speed estimated based on the above two algorithms. It can be observed from the figure that the difference between the speed estimated based on PAEKF and the actual speed is stable within plus or minus 0.5.



(**a**) (**b**)

Figure 5. (**a**) When the Q value is ⑥–⑨, the speed is estimated by the PAEKF; (**b**) when the Q value is ⑥–⑨, the speed is estimated by the EKF.



(**a**) (**b**)

Figure 6. (**a**) When the Q value is ⑥–⑨, the difference between actual speed and estimated speed based on PAEKF. (**b**) When the Q value is ⑥–⑨, the difference between actual speed and estimated speed based on EKF.

The above simulation results show that when the process noise variance Q cannot be accurately obtained, the EKF cannot reach the optimal filtering state. For example, when the estimation result converges, there is a large fluctuation, or the estimated result is quite different from the actual value and even the filter does not converge. But the velocity estimation based on PAEKF still converges under imprecise Q. Moreover, the stability and accuracy of PAEKF in estimating the convergence rate are also better than EKF. The simulation results verify the performance of PAEKF in the PMSM control system.

3.2. Simulation of PMSM Control System Based on PAEKF and Existing Parameter Adaptive Methods

In reference [22], the author constructed a parameter adaptive function. The adaptive adjustment of noise parameters is realized by adjusting the values of two parameters α

and β in the function, to improve the dynamic and steady-state performance of the PMSM closed-loop control system. Figure 7 shows the simulation results of the PMSM control system based on the adaptive law proposed in reference [22].

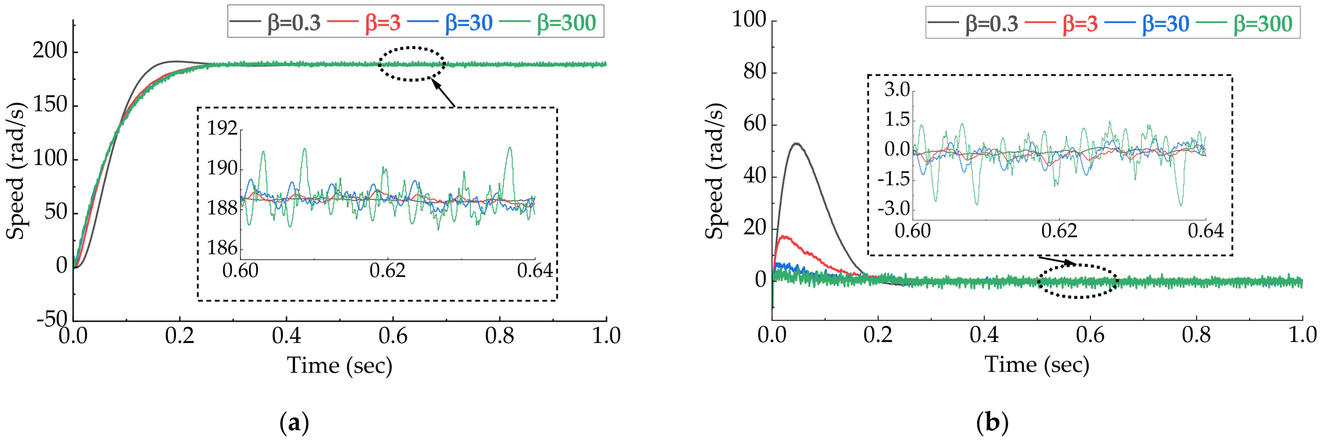


Figure 7. (**a**) Speed estimation based on the method in [22]. (**b**) The difference between the actual speed and the speed estimated is based on the method in [22].

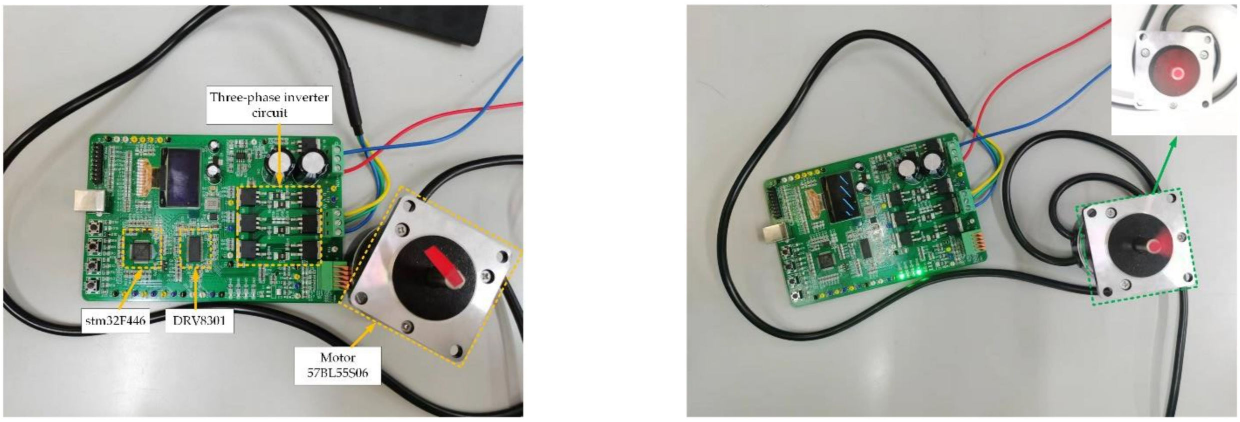
The simulation results from Figure 7 show that as the β value increases, the greater the floating of the PMSM estimation speed. In addition, although the adaptive method proposed in the literature [22] completes the adaptation of noise parameters, it also introduces additional parameters α and β. Furthermore, the selection of these parameters is also a significant work. However, the speed estimation of PMSM based on PAEKF stays within plus–minus 0.5. Therefore, the method in [22] is not as stable and accurate as the method based on PAEKF.

3.3. Experiment of PMSM Control System Based on PAEKF

This section gives the experimental results of the PMSM control system based on PAEKF. As shown in Figure 8, the experiment uses STM32F446 chip and DRV8301 three-phase gate driver as the core hardware platform to drive the 57BL55S06 series motor. The parameters of the motor are as shown in Table 3. The motor in Figure 8a is in a state of stopping, and the motor in Figure 8b is rotating. In Figure 9, Curves A and B represent the experimental results of the PMSM control system based on EKF and PAEKF when Q = diag(0.1,0.1,50,0.1), respectively. It can be seen from Figure 9 that when the accurate process noise covariance Q cannot be obtained, the PMSM control system based on PAEKF and EKF can achieve the convergence of estimation speed, but the convergence time of EKF algorithm is slower than that of PAEKF algorithm. In addition, the estimation speed of EKF algorithm fluctuates greatly when it converges, which is inferior to PAEKF algorithm in stability and accuracy.

Table 3. The 57BL55S06 series PMSM parameters.

Parameter	Values
Voltage V_{dc} (V)	24
Rated speed (r/min)	3000
Inductance L (mH)	1.4
Resistance R (Ω)	0.59
viscous damping F (N·m·s)	6.12×10^{-6}
Pole pairs p	2



(**a**) (**b**)

Figure 8. PMSM experiment platform. (**a**) the motor is in a state of stop. (**b**) the motor is in a state of rotation.

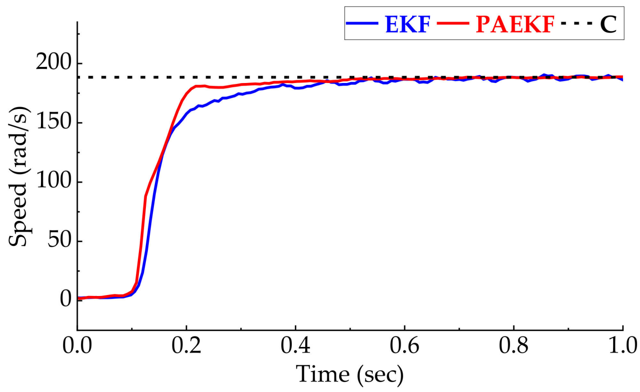
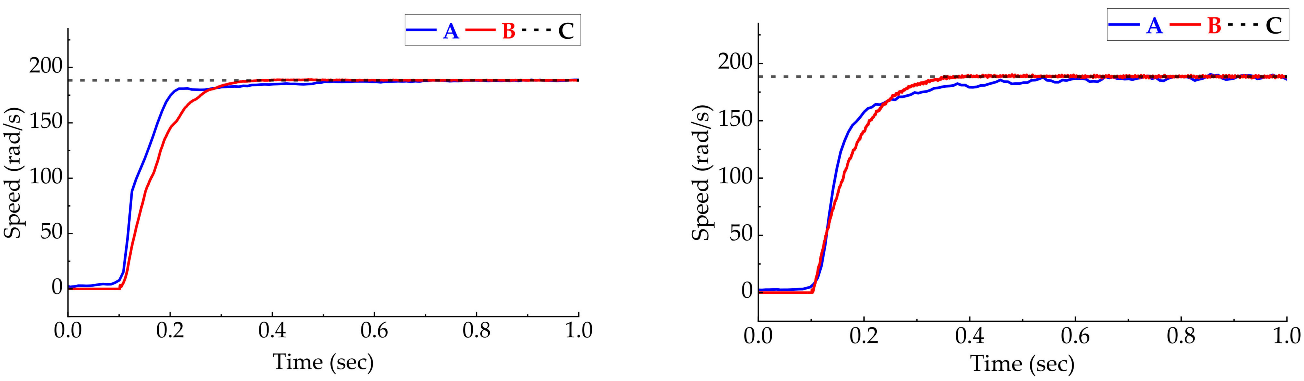


Figure 9. Experimental results of PMSM control system based on EKF and PAEKF.

As shown in Figure 10, curves A and B are experimental results and simulation results, respectively. Curve C is the set speed reference value. The experimental results show that the PMSM control system based on PAEKF can well estimate the real-time speed of the motor, effectively reduce the steady-state jitter, and improve the filtering adaptability and calculation accuracy. Moreover, it can be proved that the theoretical derivation of PMSM vector control based on PAEKF is efficient.



(**a**) (**b**)

Figure 10. (**a**) Experimental results of PMSM control system based on PAEKF; (**b**) experimental results of PMSM control system based on EKF.

4. Conclusions

To address the inaccuracy statistics process noise problem in the process of PMSM speed estimation of EKF, this paper proposes a new linear time-invariant PAEKF algorithm. The algorithm uses the posteriori sequence to predict the prior error covariance adaptively, and solves the problem of the strict restriction of the Kalman filter to the noise covariance matrix. Compared with the trial-and-error method, the method proposed in this paper saves the work of obtaining the optimal noise parameters and speeds up the development process in practice. Finally, this paper compares the proposed algorithm with the traditional EKF and the existing adaptive EKF. The simulation results show that the proposed algorithm can estimate a more accurate real-time speed of the motor, effectively reduce steady-state jitter, and improve the adaptability and the calculation accuracy of the filter.

The motor parameters (stator inductance, stator resistance, rotor flux) will change with its operation. In order to make the calculation of PAEKF more accurate and the research more complete, our future work is to think about how to complete the self-renewal of motor parameters from the inside, further improve the accuracy of sensorless algorithm, and apply it to the field of automotive electric assisted steering.

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