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Permanent Magnet Synchronous Motor with Sensorless Vector Control System based on extended Kalman filter

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Abstract: Traditional permanent magnet synchronous motor (PMSM) with servo control system reduces the stability and robustness of the system according to install the mechanical sensor to obtain the information of motor position. Therefore, we design a permanent magnet synchronous motor with servo control system based on extended Kalman filter, and the PMSM mathematical model is linearized to give an estimated position of the rotor, which is based on extended Kalman filter. The simulation results show that the algorithm based on Kalman filter can track the information of rotor position. Meanwhile, it also has the advantages of high accuracy, fast-tracking for real signals.
Keywords: PMSM, vector control system, sensor less, extended Kalman filter.

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1. INTRODUCTION

Due to the advent of rare earth permanent magnet NdFeB materials, permanent magnet motors have become the representatives of high power density and high-efficiency motors. Permanent magnet motor structure is simple, flexible control, and the various forms of rotors make it easy to optimize the design [1]. Over the past 30 years, with the development of various technologies in power electronics, intelligent power modules, VLSI circuits, and modern motor control technologies, AC servo systems have been widely used in aerospace, medical, automotive, appliances, robots, and many other fields. The current mainstream of permanent magnet synchronous motor servo control system commonly used magnetic field-oriented control or direct torque control, which require speed closed-loop to achieve high-precision and high-performance control. Meanwhile, rotor position accuracy will affect its control performance. At present, the most mature solution in the market is to obtain the rotor position speed information (optical encoder, tacho generator, resolver, hall sensor, etc.) by adding a mechanical sensor in the axial direction of the rotor. However, such sensors are poor anti-interference ability, expensive, and high installation requirements, thus limiting its application. Therefore, speed sensorless technology is becoming more and more popular in recent years. After a lot of research, the scholars put forward the following kinds of methods, which mainly: include: 1, Direct calculation method based on mathematical model, obtaining rotor speed by measuring motor voltage and current; 2, Estimating speed based on model reference adaptive system; 3, Sliding mode observer speed estimation; 4 Based on artificial intelligence control theory of speed estimation [1-3], which is according to different applications.

Some current sensorless rotor position estimation algorithms without PMSM can achieve good estimation results [4]. However, because of nonlinear characteristics of PMSM, there are many uncertainties, such as random noise [5]. In view of this, this paper has mathematically modeling for the permanent magnet synchronous motor, and utilizing rotor position recognition based on extended Kalman filter to realize the sensorless vector control system of the permanent magnet synchronous motor, the feasibility of the algorithm is verified by Matlab / Simulink simulation .

2. THE PERMANENT MAGNET SYNCHRONOUS MOTOR MATHEMATICAL MODEL IN THE STATIONARY COORDINATE SYSTEM

Surface mount three-phase permanent magnet synchronous motor voltage equation in the stationary coordinate system [6].

$$\begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} = \begin{bmatrix} R+\frac{d}{dt}L_s & 0 \\ 0 & R+\frac{d}{dt}L_s \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \omega_e \psi_f \begin{bmatrix} -\sin\theta_e \\ \cos\theta_e \end{bmatrix} \tag{1}$$

In formula (1):

u_α , u_β : Stator voltage in the $\alpha\beta$ -axis component;

i_α , i_β : Stator current in the $\alpha\beta$ -axis component;

R_s , L_s , ψ_f : stator resistance, stator inductance, rotor permanent magnet;

ω_e , θ_e : rotor electrical angular velocity, rotor electrical angle;

Mechanical motion equation is:

$$T_e = J\frac{d\omega_r}{dt} - B\omega_r + T_L \tag{2}$$

Because the sampling cycle time of permanent magnet synchronous motor is far less than the mechanical time constant, so

$$\begin{cases} \dfrac{d\omega_e}{dt} = 0 \\ \dfrac{d\theta_e}{dt} = \omega_e \\ \omega_e = N_p \omega_r \end{cases} \tag{3}$$

In formula (2):

T_e , T_L : Electromagnetic torque, load torque;

ω_r , B : Mechanical angular velocity, damping coefficient;

N_p , J : Motor pole pairs, a moment of inertia.

3. DESIGN OF EXTENDED KALMAN FILTER

The extended Kalman filter is an algorithm that uses the linear system state equation to input and outputs the observed data through the system to estimate the system state optimally. Because of the observed data includes the influence of noise and interference in the system, the optimal estimation can also be regarded as the filtering process. Now equation (1) is transformed into the current equation:

$$\begin{bmatrix} \dot{i}_\alpha \\ \dot{i}_\beta \end{bmatrix} = \begin{bmatrix} -\dfrac{R_s}{L_s} & 0 \\ 0 & -\dfrac{R_s}{L_s} \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \begin{bmatrix} \dfrac{1}{L_s} & 0 \\ 0 & \dfrac{1}{L_s} \end{bmatrix} \begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} + \begin{bmatrix} \dfrac{\psi_f N_p \omega_r}{L_s} \sin\theta_e \\ -\dfrac{\psi_f N_p \omega_r}{L_s} \cos\theta_e \end{bmatrix} \tag{4}$$

From equation (2) (3) (4) the following equation of state can be obtained:

$$\begin{cases} \dfrac{d}{dt} x = f(x) + Bu \\ y = Cx \end{cases} \tag{5}$$

In the formula:

$$x = \begin{bmatrix} i_\alpha & i_\beta & \omega_e & \theta_e \end{bmatrix}^T, \ u = \begin{bmatrix} u_\alpha & u_\beta \end{bmatrix}^T, \ y = \begin{bmatrix} i_\alpha & i_\beta \end{bmatrix}^T;$$

$$f(x) = \begin{bmatrix} -\dfrac{R_s}{L_s} i_\alpha + \omega_e \dfrac{\psi_f}{L_s} \sin\theta_e \\ -\dfrac{R_s}{L_s} i_\beta - \omega_e \dfrac{\psi_f}{L_s} \cos\theta_e \\ 0 \\ \omega_e \end{bmatrix} \quad B = \begin{bmatrix} \dfrac{1}{L_s} & 0 \\ 0 & \dfrac{1}{L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

To linearize $f(x)$, which is $\dfrac{\partial f(x)}{\partial x}$, get the Jacobian matrix:

$$F=\begin{bmatrix} -\frac{R_s}{L_s} & 0 & \frac{\psi_f \sin\theta_e}{L_s} & \frac{\psi_f \omega_e \cos\theta_e}{L_s} \\ 0 & -\frac{R_s}{L_s} & -\frac{\psi_f \cos\theta_e}{L_s} & \frac{\psi_f \omega_e \sin\theta_e}{L_s} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

When using the EKF observer, since the mathematical model of the PMSM motor is continuous at this time, it is necessary to discretize it. The set sampling period is T_s, The formula (5) is transformed into:

$$\begin{cases} x(k+1)=(T_sF+1)x(k)+B(k)T_su(k)\}+V(k) \\ y(k)=C(k)x(k)+W(k) \end{cases} \tag{6}$$

In formula (6) $V(k)$, $W(k)$ respectively are System noise and measurement noise. They are white noise, and their mathematical expectations are zero, $E\{V(k)\}=0$ and $E\{W(k)\}=0$, and they are not related.

Covariance matrix: $\begin{cases} \operatorname{cov}(V)=E\{VV^T\}=Q \\ \operatorname{cov}(W)=E\{WW^T\}=R \end{cases}$

EKF state estimation is divided into two phases: state prediction, state update.

(1) State prediction stage

First, according to the input value and state transition matrix at moment k, we estimate the prior estimate of the state variables at moment $k+1$

$$\tilde{x}(k+1)=(1+FT_s)\hat{x}(k)+B(k)T_su(k)$$

$$\tilde{y}(k+1)=C\tilde{x}(k+1)$$

"^" represents the state estimate, "~" represents the predicted value.

Utilizing the state transition matrix and the error covariance matrix estimated at moment k, the predict error covariance matrix at moment $k+1$ is obtained, which is expressed as the transfer of uncertainty in each moment.

$$\tilde{P}(k+1)=(1+FT_s)\hat{P}(1+FT_s)^T+Q$$

(2) State update phase

The Kalman coefficient (gain matrix) is calculated from the predicted error covariance matrix and the observation matrix $C(k)$.

$$K(k+1)=\tilde{P}(k+1)C^T[C\tilde{P}(k+1)C^T+R]^{-1}$$

The optimal estimate at moment $k+1$ can be obtained

$$\hat{x}(k+1)=\tilde{x}(k+1)+K(k+1)[y(k+1)-C\tilde{x}(k+1)]$$

Update the optimal error covariance required for the next estimation

$$\hat{p}(k+1) = [I - K(k+1)C(k+1)]\tilde{p}(k+1)$$

It should be noted that the selection of the system noise covariance matrix Q and the measurement noise matrix R during EKF implementation will affect the convergence of the algorithm. In this paper, the noise matrix suitable for the system is finally determined through multiple simulation experiments and personal experiences. It is noteworthy that EKF-based sensorless vector control systems can operate over a wide range of speeds, but it will lose control at zero velocities because the stator voltage becomes very small at this point, with the uncertainty of errors in the pre-measurement and the motor model will be prominent, which will lead to an increase of error in state estimation [4].

In this system, the speed loop, the current loop all use the PI controller to carry on the adjustment, use the vector control method. System structure is shown in Fig 1:

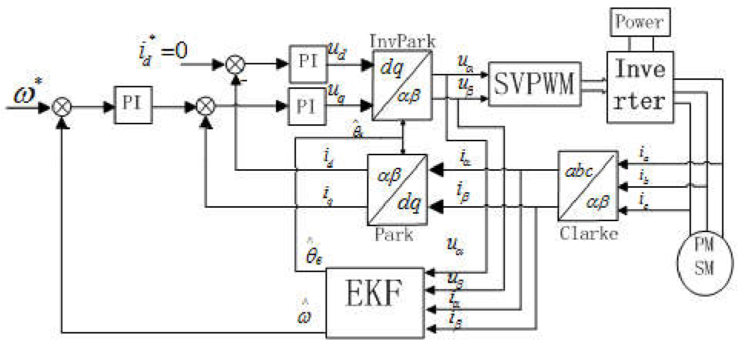

Fig. 1 Permanent Magnet Synchronous Motor Vector Control System Based on Extended Kalman Filter

4. SIMULATION AND VERIFICATION

This paper carries on the simulation test in the Simulink and Matlab, the simulation motor parameters are: stator resistance $R = 2.875\Omega$; stator inductance $L_s = 0.0085H$, pole pairs $N_p = 4$, flux $\psi_f = 0.175Wb$, a moment of inertia $J = 0.003kg \cdot m^2$, damping coefficient $B = 0$ .Select the EKF parameters as following: $x_0 = [0 \quad 0 \quad 0 \quad 0]$, $P_0 = \text{diag}\ ([0.1 \quad 0.1 \quad 0 \quad 0])$, $Q = diag([0.1 \quad 0.1 \quad 5 \quad 0.01])$, $R = [0.5 \quad 0.5]$, Start the motor under a no-load condition with given speed 500r / min. Set the simulation time 0.4s, the motor starts with no load.

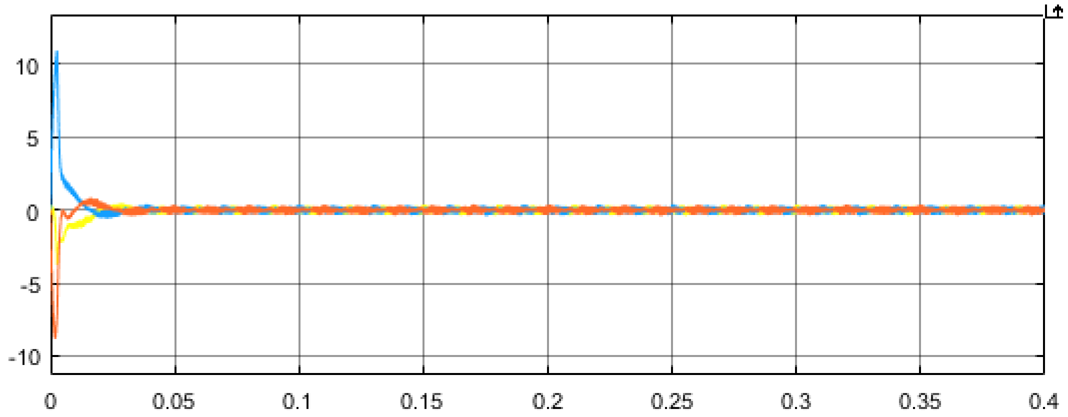

Fig. 2 three-phase current when the motor is running

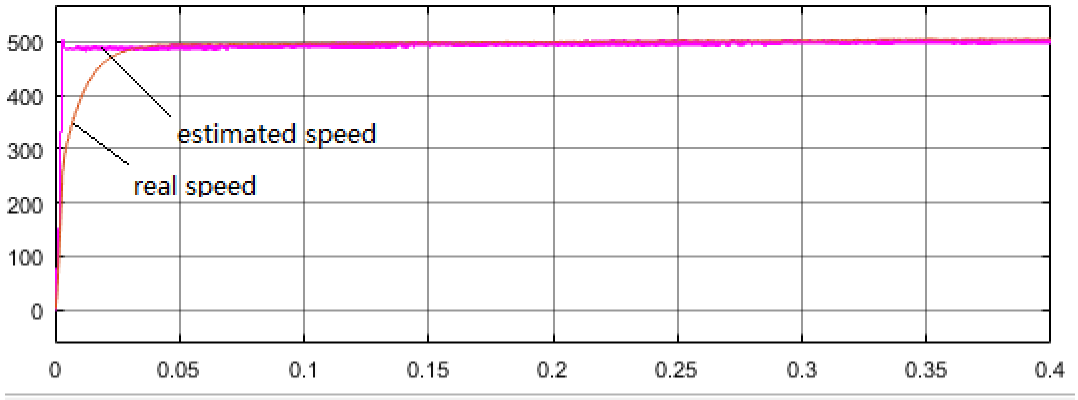

Fig. 3 estimated speed and real speed curve

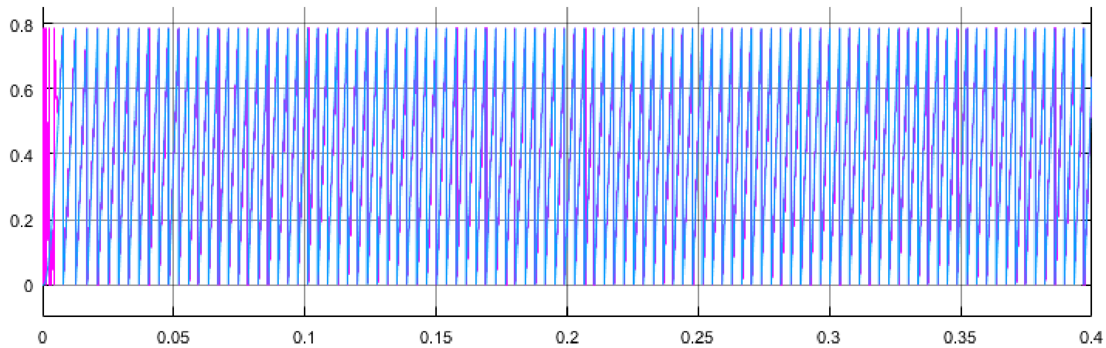

Fig. 4 rotor estimated angle and the real rotor angle

Fig 3 shows that at time 0.05s, the system has reached a steady state with a steady current. It can be seen from Fig 4 and Fig 2 that due to the relatively large system noise error in the initial stage, there is a start-up error during the start-up phase. However, as the covariances of two kinds of errors are updated continuously and iteratively, the errors become smaller and smaller, making the estimation closer to the real value. Eventually, it will reach the goal which making the system meet the control requirements in a short time.

5. CONCLUSION

This paper designs a sensorless vector control system of the permanent magnet synchronous motor based on extended Kalman filter. The simulation results show that the system can obtain the accurate rotor position quickly by selecting the appropriate system error covariance matrix and the measurement noise covariance matrix. It can also obtain better dynamic and static performance and realize the sensorless vector control.

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