

Speed Sensorless Vector Control of Induction Motor Based on Reduced Order Extended Kalman Filter

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Abstract: A speed sensorless vector control system of induction motor with estimated rotor speed and rotor flux using a new reduced-order extended Kalman filter is proposed. With this method, two rotor flux components are selected as the state variables, and the rotor speed as an estimated parameter is regarded as an augmented state variable. The algorithm with reduced order decreases the computational complexity and makes the proposed estimator feasible to be implemented in real time. The simulation results show high accuracy of the estimation algorithm and good performance of speed control, and verify the usefulness of the proposed algorithm.

Key words: extended Kalman filter, flux estimation, speed estimation, speed sensorless vector control, induction motor

The vector-controlled induction motor drives are now increasingly being used in industry applications. In drive systems, generally, speed sensors such as shaft-mounted resolvers or digital shaft position encoders are used to measure the rotor speed. The sensors degrade the system's reliability, and spoil the general characteristics of ruggedness and mechanical simplicity of the induction motor. From this regard, a speed sensorless system is preferred. Therefore, many kinds of vector-controlled induction motor drives without speed sensors have been proposed. The traditional approaches of speed sensorless vector control use the flux and slip estimation with stator currents and voltages^[1], but they have a large error in speed estimations, particularly in the low speed range. The methods of MRAS (model reference adaptive system) are also applied to estimate the rotor speed of the induction motor^[2]. These also have a speed error in the low speed range and settle to an incorrect steady state value. Recently, the Kalman filter algorithm has been employed for the parameter estimation of induction motor^[3], or for the speed estimation of synchronous and induction motor^[4]. In [4], to estimate the rotor speed of induction motor using an extended Kalman filter, not only the angular rotor speed but also the angular rotor flux frequency and the rotor flux angle have to be augmented in the extended Kalman filter because only the stator currents and magnetizing current are chose as state variables. The complete decoupling of d - q flux components and the constant magnetizing current is assumed. In [5], a speed sensorless vector control is presented, which

uses a fifth-order extended Kalman filter with two rotor flux components and two stator current components as state variables and the rotor speed as an estimated parameter to estimate the rotor flux and rotor speed. Although no assumption of decoupling of d - q flux components and the constant magnetizing current, it appears very complex because of the high order of the extended Kalman filter. The applicability of the Kalman filter to real-time signal processing problems is generally limited by the complex mathematical operations such as the matrix inversion necessary in computing the designed algorithm. This paper proposes a new reduced-order extended Kalman filter that only uses two rotor flux components as state variables and the rotor speed as an estimated parameter. Order reduction simplifies the computation problem and makes it feasible to implement Kalman filter in real time with digital signal processing (DSP) processors.

1 Induction Motor Model

The expression of mathematical model of induction motor can be simplified considerably by the use of complex vector notation. In general, the complex vector are written in the form, $f_{\alpha\beta} = f_{\alpha} + jf_{\beta}$. Therefore, in the stationary reference frame α - β , the stator and rotor voltage equations of the induction motor are written as follows:

$$p\psi_{s\alpha\beta} = v_{s\alpha\beta} - R_s i_{s\alpha\beta} \quad (1)$$

$$p\psi_{r\alpha\beta} = -(1/T_r - j\omega_r)\psi_{r\alpha\beta} + (1/T_r)L_m i_{s\alpha\beta} \quad (2)$$

where p is the operator d/dt ; R_s is the stator resistance; $T_r = L_r/R_r$, R_r is the rotor resistance; L_r

is the rotor inductance; ω_r is the electrical angular speed of the rotor; $\sigma = 1 - L_m^2/L_s L_r$; L_s is the stator inductance; L_m is the magnetizing inductance, and

$$\psi_{s\alpha\beta} = \frac{L_m}{L_r} \psi_{r\alpha\beta} + \sigma L_s i_{s\alpha\beta} \quad (3)$$

The motion equation of the inductor motor is described by

$$p\omega_r = n_p(T_e - T_L)/J - R_\omega \omega_r/J \quad (4)$$

where J is the moment of inertia of the rotor and connected mechanical load; R_ω is the damping coefficient; T_L is the load torque; and n_p is the number of pole pairs. The electro-magnetic torque T_e can be expressed as

$$T_e = n_p L_m (\psi_{ra} i_{sb} - \psi_{rb} i_{sa})/L_r \quad (5)$$

In the rotating reference frame $d-q$, oriented to the rotor flux (i.e., using rotor flux as the d -axis reference frame), the transformation between the α - β reference frame and the d - q reference frame variables is

$$[f_d f_q]^T = M [f_\alpha f_\beta]^T$$

where $M = \begin{bmatrix} \cos\rho & \sin\rho \\ -\sin\rho & \cos\rho \end{bmatrix}$, $\sin\rho = \frac{\psi_{rb}}{\psi_r}$, $\cos\rho = \frac{\psi_{ra}}{\psi_r}$, $\psi_r = \sqrt{\psi_{ra}^2 + \psi_{rb}^2}$, thus (2) and (5) may be changed as

$$p\psi_r = -\psi_r/T_r + L_m i_{sd}/T_r \quad (6)$$

$$T_e = n_p L_m \psi_r i_{sq}/L_r \quad (7)$$

From Eqs. (6) and (7), i_{sd} and i_{sq} are the rotor flux and torque-producing components of stator current. Vector control is achieved by controlling independently these two current components.

2 Reduced Order Extended Kalman Filter Algorithm

The extended Kalman filter algorithm has to be employed because not only the rotor flux but also the angular rotor speed is estimated. In this case, the angular rotor speed is considered as a parameter and an augmented state. The algorithm requires that the estimation process is described by a discrete-time state space model and the corresponding observation equation.

It is possible to assume that the estimation process is governed by the “current model” which is (2). The angular rotor speed is regarded as an additional parameter and is estimated in conjunction with the rotor flux components, thus a further equation must be appended to (2). Assuming the sampling time T is small enough in comparison with the considered

response time, the speed may be considered constant within one sampling time. As a consequence, the motion equation of induction motor (4) is reduced to

$$p\omega_r = 0 \quad (8)$$

Eqs. (2) and (8) can be discretized by the Euler method, and the complete model of estimation process becomes:

$$\begin{aligned} \psi_{r\alpha\beta}(n+1) &= [1 - (1/T_r - j\omega_r)T] \psi_{r\alpha\beta}(n) \\ &\quad + (T/T_r) L_m i_{s\alpha\beta}(n) + \varepsilon_\psi(n) \end{aligned} \quad (9)$$

$$\omega_r(n+1) = \omega_r(n) + \varepsilon_\omega(n) \quad (10)$$

where $\varepsilon_\psi = \varepsilon_{\psi\alpha} + j\varepsilon_{\psi\beta}$ and ε_ω are the model noises.

Eqs. (9) and (10) may be rewritten in matrix form as follows:

$$x(n+1) = f(x(n), u(n), n) + \varepsilon \quad (11)$$

where $x = [\psi_{ra} \psi_{rb} \omega_r]^T$, $f = [f_1 f_2 f_3]^T$, $u(n) = [i_{sa} i_{sb}]^T$, and $\varepsilon = [\varepsilon_{\psi\alpha} \varepsilon_{\psi\beta} \varepsilon_\omega]^T$ is the model noise.

The following observation equation is obtained after substituting Eq. (3) into (1) and being discretized

$$\begin{aligned} y_{\alpha\beta}(n+1) &= \psi_{r\alpha\beta}(n+1) - \psi_{r\alpha\beta}(n) \\ &\quad + v_{\alpha\beta}(n+1) \end{aligned} \quad (12)$$

where $y_{\alpha\beta}(n+1) = y_\alpha(n+1) + jy_\beta(n+1)$ is the measurement at time instant $(n+1)$ given by

$$\begin{aligned} y_{\alpha\beta}(n+1) &= T \frac{L_r}{L_m} [v_{s\alpha\beta}(n) - R_s i_{s\alpha\beta}(n)] \\ &\quad - \frac{\sigma L_r L_s}{L_m} [i_{s\alpha\beta}(n+1) - i_{s\alpha\beta}(n)] \end{aligned}$$

and $v_{\alpha\beta}(n+1) = v_\alpha(n+1) + jv_\beta(n+1)$ is the measurement noises. The matrix representation of Eq. (12) becomes

$$y(n+1) = Hx(n+1) + Jx(n) + v(n+1) \quad (13)$$

where $y = [y_\alpha y_\beta]^T$, $H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$

$$J = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \end{bmatrix}, \quad v = [v_\alpha v_\beta]^T$$

The model noise ε and the measurement noise v are assumed to be zero-mean white Gaussian and uncorrelated noises. The covariance of ε and v are Q and N , respectively. $x(0)$ is assumed to be the initial condition with mean x_0 and covariance P_0 . From Eq. (13), $y(n+1)$ is determined by not only $x(n+1)$ but also $x(n)$, so the delayed state filter algorithm of Kalman filter has to be employed.

The extended Kalman filter prediction equation is given by (14)

$$\hat{x}(n+1/n) = f(\hat{x}(n/n), u(n), n) \quad (14)$$

The covariance matrix of the prediction error is as follows:

$$P(n+1/n) = \varphi(n+1/n)P(n/n)\varphi^T \times (n+1/n) + Q \quad (15)$$

$$\text{where } \varphi(n+1/n) = \left. \frac{\partial f(x(n), u(n), n)}{\partial x(n)} \right|_{x(n) = \hat{x}(n/n)}$$

The Kalman gain is given by (16)

$$K(n+1) = (P(n+1/n)H^T + \varphi(n+1/n) \times P(n/n)J^T [HP(n+1/n)H^T + N + JP(n/n)J^T + H\varphi(n+1/n) \times P(n/n)J^T + JP(n/n)\varphi^T \times (n+1/n)H^T]^{-1} \quad (16)$$

The covariance matrix of the estimation error may be computed as follows:

$$P(n+1/n+1) = P(n+1/n) - K(n+1)L(n+1)K^T(n+1) \quad (17)$$

where $L(n+1)$ is the bracketed term of Eq. (16) (not inverted).

The state estimation of the extended Kalman filter is described by (18)

$$\hat{x}(n+1/n+1) = \hat{x}(n+1/n) + K(n+1) \times [y(n+1) - H\hat{x}(n+1/n) - J\hat{x}(n/n)] \quad (18)$$

Eqs. (14) – (17), and Eq. (18) are the recursive equations of “the delayed Kalman filter algorithm”^[6].

3 Speed Sensorless Vector Control System Configuration

Fig.1 shows a direct vector control system

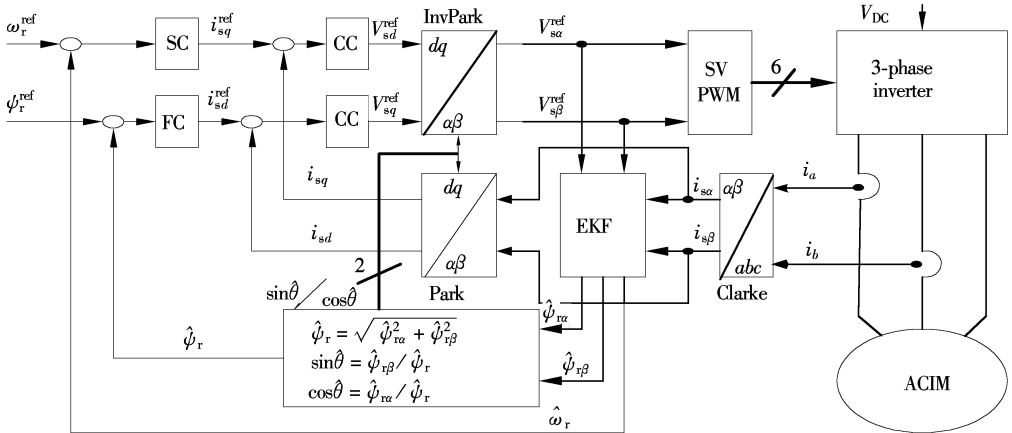


Fig.1 Block diagram of the direct vector control system

4 Simulation Results

To verify the effectiveness of speed and rotor flux estimation method, computer simulations have been carried out by using the Matlab/Simulink. The Simulink model of the speed sensorless vector control system shown in Fig.1 is realized. In this model, the EKF and PWM signal generator SVPWM are implemented as two S-functions. The parameters of the

actual motor used in this simulation study are given as follows: rated power $P_n = 500$ W, rated voltage $V_n = 220$ V, rated current $I_n = 2.9$ A, rated frequency $f_n = 50$ Hz, pole number = 4, rated slip 0.066, stator resistance $R_s = 4.495 \Omega$, rotor resistance $R_r = 5.365 \Omega$, stator inductance $L_s = 0.165$ H, rotor inductance $L_r = 0.162$ H, magnetizing inductance $L_m = 0.149$ H, rotor inertia $0.00095 \text{ kg} \cdot \text{m}^2$. The Kalman filter is useful in the system that has system noise and

accomplished by estimating the rotor flux components and rotor speed through extended Kalman filter algorithm using the voltage references and measured stator currents. In this system, the current references $i_{sd}^{\text{ref}}, i_{sq}^{\text{ref}}$ are supplied by the flux controller FC and speed controller SC, respectively. The rotor speed $\hat{\omega}_r$ and rotor flux $\hat{\psi}_r$ estimated by the Kalman filter EKF are regarded as the feedback values of rotor speed and rotor flux. The current control is performed at the synchronously rotating reference frame $d-q$. Therefore, the steady-state error and phase delay are minimized^[7]. The sine and cosine of the rotor flux angle for the transformation between the synchronously rotating reference frame $d-q$ and the stationary reference frame $\alpha-\beta$ is calculated by the estimated rotor flux components $\hat{\psi}_{ra}, \hat{\psi}_{r\beta}$ from EKF. The method of space voltage vector PWM is used to generate the six pulsed signal. The reference voltages $V_{sa}^{\text{ref}}, V_{sb}^{\text{ref}}$ are used in the Kalman filter algorithm as stator voltages without measurement since in this current control method the reference voltages are about as the same as the actual voltages under the assumption of dead time compensation. Thus, in this system, the stator voltages are not to be measured, only the stator currents are measured.

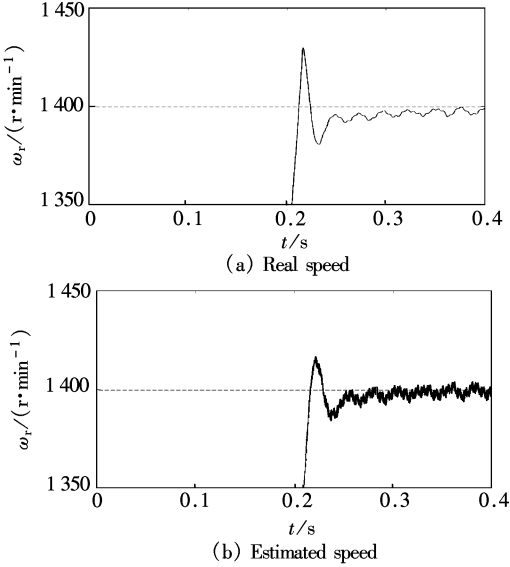


Fig.2 $\omega_r^{\text{ref}} = 1\,400\text{ r/min}$

measurement noise. Therefore, the effect of noises is included in this simulation. The system noise covariance Q is $10^{-4}\text{diag}(1\ 1\ 1)$ and measurement noise covariance N is $10^{-4}\text{diag}(2\ 2)$. Fig.2 shows the real speed and the estimated speed when the speed reference ω_r^{ref} is 1 400 r/min. The estimated speed means the speed that is estimated using a reduced order extended Kalman filter. The real speed is known from the estimation variable because it is the estimation. The speed error between the real speed and the estimated speed is within a few revolutions per minute. At $t = 0.22\text{ s}$, load rated torque is applied. The speed control is performed by the estimated speed, and the speed has reached the reference speed very well. Fig.3

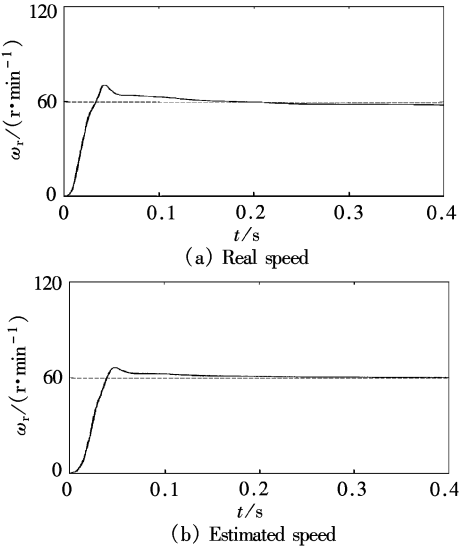


Fig.3 $\omega_r^{\text{ref}} = 60\text{ r/min}$

shows the real speed and the estimated speed when the speed reference ω_r^{ref} is 60 r/min. Also in this case, the speed error is within a several revolutions per minute. The real rotor flux and the estimated rotor flux are

shown in Fig.4 when the rotor flux reference ψ_r^{ref} is

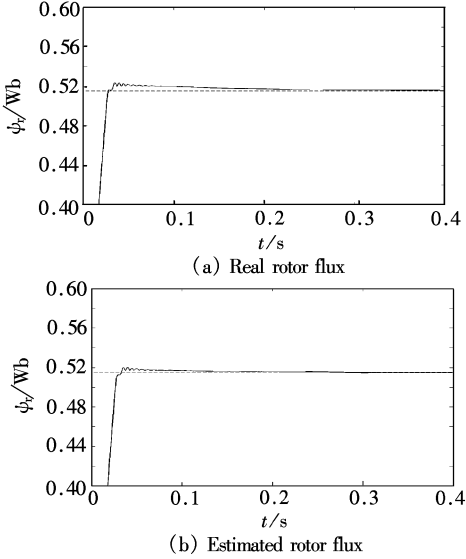


Fig.4 $\psi_r^{\text{ref}} = 0.515\text{ Wb}$

0.515 Wb and the speed reference ω_r^{ref} is 60 r/min. The rotor flux is estimated accurately. The case with the speed reference ω_r^{ref} of 1 400 r/min is almost the same. Fig.5 shows acceleration characteristics when the speed reference rises from 0 to 1 400 r/min and the response of speed reversal when the speed reference is

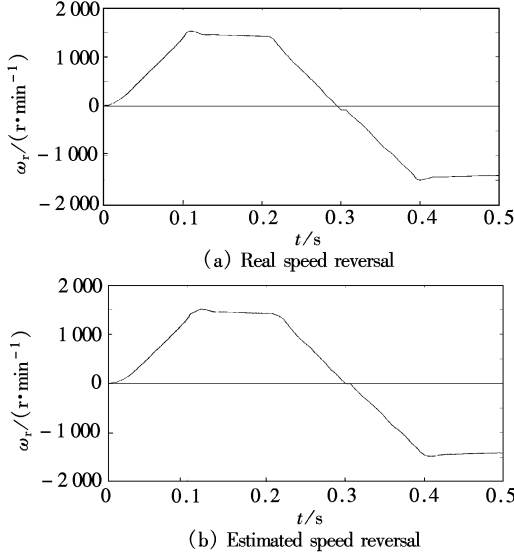


Fig.5 $\omega_r^{\text{ref}} = 1\,400 \sim -1\,400\text{ r/min}$

varied from 1 400 to $-1\,400\text{ r/min}$. It can be found that the speed response is considerably quick and the speed error is within a few revolutions. In [5], every computation the five-order extended Kalman filter algorithm needs about 1 120 operations of addition and multiplication, and every computation of the reduced order extended Kalman filter algorithm needs only about 510 operations with savings of more than 50 percent.

5 Conclusions

The paper has shown the application of reduced order extended Kalman filter to speed sensorless vector control of induction motor. Significant savings in computational requirements are obtained because of the order reduction. The estimation error of speed is within a few revolutions per minute, even at fairly low speed. The speed control and vector control with estimated speed and rotor flux produce a desirable performance over wide speed range. The speed response is good enough to use in a variable speed control. These make the proposed algorithm feasible to be used for practical applications. Further, the estimation of lower speed and the parameter dependency of estimation accuracy need to be studied.

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基于降阶推广卡尔曼滤波器的异步电机
无速度传感器矢量控制

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摘 要 提出一种估计异步电机转子速度和转子磁链的新型降阶推广卡尔曼滤波器算法,建立了基于此算法的异步电机无速度传感器矢量控制系统.以转子磁链的两个分量为状态变量,被估计的参数转子速度作为扩充状态变量,构成三阶推广卡尔曼滤波器算法,算法阶数的降低明显地减少了运算量,适合实时实现.仿真结果显示转子速度和转子磁链的估计精度高,系统的速度控制性能令人满意,证明此算法有效可行.

关键词 推广卡尔曼滤波器, 磁链估计, 速度估计, 无速度传感器矢量控制, 异步电机

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