'96 대한전기학회 하계학술대회 논문집 (1996. 7. 22~24)

이산 적응 관측자를 이용한 유도전동기의 회전자 속도 추정

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Induction motor rotor speed estimation using discrete adaptive observer

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ABSTRACT

This paper presents a discrete adaptive observer for MIMO system of an IM model in DQ reference model. The IM model in the stationary frame is discretized and it is transformed into the canonical observer form. The unknown parameter is choosen as rotor speed. The adaptive law for parameter adjustment is obtained as a set of recursive equations which are derived by utilizing an exponentially weighted normalized least-square method. The proposed adaptive observer converges rapidly and is also shown to track time-varying plant parameter quickly. Its effectiveness has been demonstrated by computer simulation.

1. INTRODUCTION

Vector controller without speed transducer has been developed. However some problem exists in each estimation method. Some method are speed range dependent and others are parameter variation dependent.[1] So they are not sufficient to apply in the general case. In this paper, the proposed adaptive observer method is applicable whole speed range. The use of adaptive control technique in the field oriented control stratagy is becoming a very intresting research area and has been investigated by [3,4,5]. In a previous paper the authors have showns that by carefully selecting the machine model one can solve the problem of parameter estimation of an IM model using linear models. In this paper, the IM model is transformed into the observer form and the state variable filter is introduced to find the linear output model. The model and adaptive law are discrete form, so it is proper to digital implementation.

2. INDUCTION MOTOR MODELING

In the stationary reference frame, both the stator and rotor voltage equations are described as follows[5]:

$$v_s = R_s i_s + \frac{d\lambda_s}{dt} \qquad v_r e^{-j\omega_r t} = R_r i_r e^{-j\omega_r t} + \frac{d(\lambda_r e^{-j\omega_r t})}{dt}$$

where v_s, v_r, i_s, i_r, λ_s, λ_r are stationary reference frame quantities. The linkage flux of stator and rotor is represented as $\lambda_s = L_s i_s + L_m i_r$, $\lambda_r = L_m i_s + L_r i_r$. We can find IM dynamic state equation.

$$\dot{x} = Ax + Bu, \quad y = Cx$$

$$x = [\, i_{ds}\ i_{qs}\ \lambda_{dr}\ \lambda_{qr}]^T,\ y = [\, i_{ds}\ i_{qs}]^T,\ u = [\, v_{ds}\ v_{qs}]^T$$

Finally we have following discrete state equation.

$$x(k+1) = Fx(k) + Gu(k), \quad y(k) = Hx(k)$$

$$F = e^{AT} \cong I + AT = \begin{bmatrix} 1-a & 0 & bd & b\omega \\ 0 & 1-a & -b\omega & bd \\ c & 0 & 1-d & -\omega \\ 0 & c & \omega & 1-d \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$G = A^{-1}(e^{AT} - I)B \cong (2I + AT)\frac{BT}{2} = \frac{e}{2}\begin{bmatrix} 2-a & 0 \\ 0 & 2-a \\ c & 0 \\ 0 & c \end{bmatrix}$$

Parameters with sampling time T are summarized as,

$$a = \left(\frac{1}{\sigma\tau_s} + \frac{1-\sigma}{\sigma\tau_r}\right)T, \quad b = \frac{1-\sigma}{\sigma L_m}, \quad c = \frac{L_m}{\tau_r}T, \quad d = \frac{1}{\tau_r}T,$$

$$e = \frac{1}{\sigma L_s}T, \quad \omega = \omega_r T$$

3. CANONICAL OBSERVER FORM

If we compare i_{ds} output system with i_{qs} output system, then we observer that each parameter vectors has similar form. So, we described the canonical observer form as follows.

For i_{ds} output system :

$$x_d(k+1) = Fx_d(k) + g_1 u_1(k) + g_2 u_2(k), \quad y_d(k) = h^T k_d(k)$$

For i_{ds} output system :

$$x_q(k+1) = Fx_q(k) - g_2 u_1(k) + g_1 u_2(k), \quad y_q(k) = h^T k_q(k)$$

$$F = \begin{bmatrix} f_1 & 1 & 0 & 0 \\ f_2 & 0 & 1 & 0 \\ f_3 & 0 & 0 & 1 \\ f_4 & 0 & 0 & 0 \end{bmatrix}, \quad f = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \end{bmatrix} = f_n + \Delta_f 6$$

$$g_1 = [g_{11}\ g_{12}\ g_{13}\ g_{14}]^T = g_n + \Delta_{g_1}\theta$$
$$g_2 = [g_{21}\ g_{22}\ g_{23}\ g_{24}]^T = \Delta_{g_2}\theta$$

where $\theta = [\omega^2\ \omega]^T$ and $f_n, g_n, \Delta_f, \Delta_{g_1}, \Delta_{g_2}$ is known parameter matrix.

4. STATE VARIABLE FILTER

It is necessary to use a stable matrix F defined by

$$\begin{bmatrix} p_1 & 1 & 0 & 0 \\ p_2 & 0 & 1 & 0 \\ p_3 & 0 & 0 & 1 \\ p_4 & 0 & 0 & 0 \end{bmatrix}, \quad p = [p_1\ p_2\ p_3\ p_4]^T.$$

Using the above stable matrix F, the stable equation is rewritten as

$$x_d(k+1) = Fx_d(k) + (f-p)y_d(k) + g_1 u_1(k) + g_2 u_2(k),\ x_d(0) = x_{d0}$$

Now define the 4×4 matrices $S_i(k)$ as the solutions of the following discrete state equations.

$$S_i(k+1) = PS_i(k) + I_4 u_i(k),\quad S_i(0) = 0$$

where I_4 is 4×4 identity matrix. $x_d(k)$ can be solved by inverse Z-transformation and above filter solutions are involved.

$$x_d(k) = [S_{y_1}(k)\ S_{u_1}(k)\ S_{u_2}(k)] \begin{bmatrix} \Delta f \\ \Delta g_1 \\ \Delta g_2 \end{bmatrix} \theta + [S_{y_1}(k)\ S_{u_1}(k)\ S_{u_2}(k)] \begin{bmatrix} f_n \\ g_n \\ 0 \end{bmatrix} + P^k x_{d0}$$

Now define 4-dimensional vectors $\phi_i(k)$ as $\phi_i(k) = S_i(k)^T h$. Output is expressed as following.

$$y_d(k) = h^T x_d(k) = \begin{bmatrix} \phi_{y1}(k) \\ \phi_{u1}(k) \\ \phi_{u2}(k) \end{bmatrix}^T \begin{bmatrix} \Delta_f \\ \Delta_{g1} \\ \Delta_{g2} \end{bmatrix} \theta + \begin{bmatrix} \phi_{y1}(k) \\ \phi_{u1}(k) \\ \phi_{u2}(k) \end{bmatrix}^T \begin{bmatrix} f_n - p \\ 0 \\ g_n \end{bmatrix} + h^T P^k x_{d0}$$

It is noted here that $S_i(k)$ and F are commutable : that is $S_i(k)P = PS_i(k)$. Using the comutativity of $S_i(k)$ and F, the vector $\phi_i(k)$ satisfies the following equation.

$$\begin{aligned} \phi_i(k+1) &= S_i(k+1)^T h = (PS_i(k))^T h + (I_n u_i(k))^T h \\ &= P^T (S_i(k))^T h + I_n h u_i(k) = P^T \phi_i(k) + h u_i(k) \end{aligned}$$
$$\phi_i(0) = S_i(0)^T h = 0$$

which described the state variable filter. Now it is also useful to construct observer based upon another output i_{qs}.

$$x_q(k+1) = Px_q(k) + (f-p)y_q(k) - g_2 u_1(k) + g_1 u_2(k)$$
$$x_q(0) = x_{q0}$$

Now two scalar output y_d and y_q can be assembled into one vector form.

$$\hat{x}(k) = S(k)\hat{\theta}(k) + P^k \hat{x}(0)$$
$$\hat{y}(k) = \Psi^T(k)\hat{\theta}(k) + h^T P^k \hat{x}(0)$$

$$\hat{x}(k) = \begin{bmatrix} \hat{x}_d(k) \\ \hat{x}_q(k) \end{bmatrix} - \begin{bmatrix} S_{y1}(k) & S_{u1}(k) \\ S_{y2}(k) & S_{u2}(k) \end{bmatrix} \begin{bmatrix} f_n - p \\ g_n \end{bmatrix}$$
$$\hat{y}(k) = \begin{bmatrix} \hat{y}_d(k) \\ \hat{y}_q(k) \end{bmatrix} - \begin{bmatrix} \phi_{y1}(k) & \phi_{u1}(k) \\ \phi_{y2}(k) & \phi_{u2}(k) \end{bmatrix}^T \begin{bmatrix} f_n - p \\ g_n \end{bmatrix}$$

where

$$\Psi(k) = [\phi_d(k)\ \phi_q(k)] = \begin{bmatrix} \Delta_f \\ \Delta_{g1} \\ \Delta_{g2} \end{bmatrix}^T \begin{bmatrix} \phi_{y1}(k) & \phi_{y2}(k) \\ \phi_{u1}(k) & \phi_{u2}(k) \\ \phi_{u2}(k) & -\phi_{u1}(k) \end{bmatrix}$$

$$S(k) = \begin{bmatrix} s_d(k) \\ s_q(k) \end{bmatrix} = \begin{bmatrix} s_{y1}(k) & s_{u1}(k) & s_{u2}(k) \\ s_{y2}(k) & s_{u2}(k) & -s_{u1}(k) \end{bmatrix} \begin{bmatrix} \Delta_f \\ \Delta_{g1} \\ \Delta_{g2} \end{bmatrix}$$

$$\hat{\theta}(k) = \begin{bmatrix} \hat{\omega}_r^2(k) \\ \hat{\omega}_r(k) \end{bmatrix}$$

The adaptive observer should be designed so as to guarantee that $\lim_{k\to+\infty}\hat{\theta}(k) = \theta$, $\lim_{k\to+\infty}\hat{x}(k) = x$.

The objective can be achieved by adjusting $\hat{\theta}(k)$ so that $\hat{y}(k)$ converges to $y(k)$. In the following, we derive an adaptive law for adjusting $\hat{\theta}(k)$ based on the exponentially weighted least-squares method.

5. ADAPTIVE LAW

To evaluate the deviation between the plant and the observer, we introduce the following criterion function. λ is a weighting coefficient given as $0<\lambda<1$.

$$J(k) = \frac{1}{2}\sum_{j=1}^{k} \lambda^{2(k-j)} [y(j) - \hat{y}(j)]^T [y(j) - \hat{y}(j)]$$

Note that the criterion function reduces to the actual output error $y(j) - \hat{y}(j)$ if $\hat{\theta}(k)$ is constant.

$$\hat{y}(j) = \Psi^T(j)\hat{\theta}(k) + h^T P^k \hat{x}_0$$

After replacing $\hat{y}(j)$ into above criterion function, we obtain following equation.

$$z_d(j) = y_d(j) - h^T P^k \hat{x}_d(0),\quad z_q(j) = y_q(j) - h^T P^k \hat{x}_q(0)$$
$$J(k) = \frac{1}{2}\sum_{j=1}^{k} \lambda^{2(k-j)} \left([z_d(j) - \phi_d^T(j)\hat{\theta}(k)]^2 + [z_q(j) - \phi_q^T(j)\hat{\theta}(k)]^2 \right)$$

The estimation $\hat{\theta}(k)$ is determined so that the criterion $J(k)$ becomes minimum at time k. Letting the gradient of $J(k)$ with respect to $\hat{\theta}(k)$ be zero yields:

$$\sum_{j=1}^{k} \lambda^{2(k-j)} [\phi_d(j) z_d(j) + \phi_q(j) z_q(j)] = \sum_{j=1}^{k} \lambda^{2(k-j)} [\phi_d(j)\phi_d^T(j) + \phi_q(j)\phi_q^T(j)]\hat{\theta}(k)$$

Defining $(12\times k)$-dimensional matrix $\Psi_d(\lambda,k)$, $\Psi_q(\lambda,k)$ and k-dimensional vector $z_d(\lambda,k)$, $z_q(\lambda,k)$ as

$$\Psi_{d,q}(\lambda,k) = [\lambda^{k-1}\phi_{d,q}(1)\ \ \lambda^{k-2}\phi_{d,q}(2)\ \cdots\ \phi_{d,q}(k)]$$
$$z_{d,q}(\lambda,k) = [\lambda^{k-1} z_{d,q}(1)\ \ \lambda^{k-2} z_{d,q}(2)\ \cdots\ z_{d,q}(k)]^T$$

Using above defined matrix and vector, we can obtain following parameter finding equation.

$$\Psi(\lambda,k)\Psi(\lambda,k)^T\hat{\theta}(k) = \Psi(\lambda,k) z(\lambda,k)$$

Therefore, if the matrix $\Psi(\lambda,k)\Psi(\lambda,k)^T$ is invertible, the estimated $\hat{\theta}(k)$ which minimizes $J(k)$ is given by

$$\hat{\theta}(k) = [\Psi(\lambda,k)\Psi(\lambda,k)^T]^{-1}\Psi(\lambda,k)z(\lambda,k)$$

$$= \Gamma(\lambda,k)\Psi(\lambda,k)z(\lambda,k)$$

The parameter update law is obtained as following recursive equation.

$$\hat{\theta}(k+1) = \hat{\theta}(k) + \Gamma(\lambda,k+1)\Psi(k+1)[z(k+1) - \Psi(k+1)^T\hat{\theta}(k)]$$

$$\Gamma(\lambda,k) = \frac{\Gamma(\lambda,k)}{\lambda^2} - \frac{\Gamma(\lambda,k)}{\lambda^2}\Psi(k+1)\left[\Psi(k+1)^T\frac{\Gamma(\lambda,k)}{\lambda^2}\Psi(k+1) + I_2\right]^{-1}\Psi(k+1)^T\frac{\Gamma(\lambda,k)}{\lambda^2}$$

The above equations are not applicable until $k=2$, because $\Gamma(\lambda,k)$ cannot be defined for $k<2$. $\Gamma(\lambda,k)$ is not full rank for $k<2$. However, if the initial value if $\Gamma(\lambda,k)$ is set as $\Gamma(\lambda,0) = d^2 I_2$; $d \gg 1$.

The normalized least square algorithm is stable when input has nonuniform amplitude signal. Cost function is taken as normalized form.

$$J(k) = \frac{1}{2}\sum_{j=1}^{k}\lambda^{2(k-j)}\left(\frac{[z_d(j) - \phi_d^T(j)\hat{\theta}(k)]^2}{a + \phi_d^T(j)\phi_d(j)} + \frac{[z_q(j) - \phi_q^T(j)\hat{\theta}(k)]^2}{a + \phi_q^T(j)\phi_q(j)}\right)$$

The parameter update law is the same as above case. But the filter states and output is normalized.

$$\Psi(k+1) = \left[\frac{\phi_d(k+1)}{\sqrt{a + \phi_d^T(k+1)\phi_d(k+1)}} \quad \frac{\phi_q(k+1)}{\sqrt{a + \phi_q^T(k+1)\phi_q(k+1)}}\right]$$

$$z(k+1) = \left[\frac{z_d(k+1)}{\sqrt{a + \phi_d^T(k+1)\phi_d(k+1)}} \quad \frac{z_q(k+1)}{\sqrt{a + \phi_q^T(k+1)\phi_q(k+1)}}\right]^T$$

6. SIMULATION RESULT

The computer simulation is done to verify the proposed algorithm. The input voltage command was v/f = constant profile and no feedback control was involved. Motor characteristic is as follows: 3 hp, 220 Vrms, 1710 rpm, 4 pole.

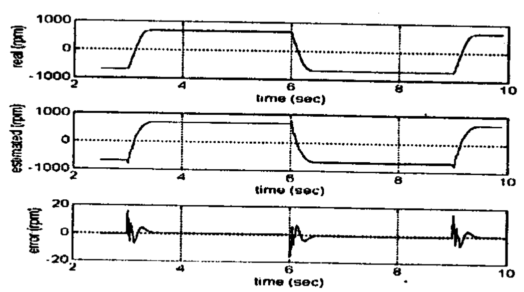

fig. 1 : estimated rotor speed and error

7. CONCLUSION

In this paper, a method for the automatic identification of induction motor speed was presented. The method is tracking rotor speed quickly. The algorithm does not depend on a specific input command profile. The algorithm is fast and can be implemented in real-time with existing hardware. The method is applicable for the design of self-tuning(self-commissing) AC drives to optimize their performance. In addition to providing parameter identification, the algorithm provides simultaneous estimated motor state variables such as rotor flux. Finally, the estimated parameter error in the paper are useful for judging the performance of the identification scheme. Simulation results indicate that the error is less than 1%.

8. REFERENCE

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