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Model Reference Adaptive Control of Induction Motor Based on Direct Torque Control

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Abstract: This paper proposes two identifiers. One is used to identify stator flux, by which the electromagnetic torque can be calculated. The other discusses dynamical identification of rotor speed under the conditions that the parameters of induction motor are unchanged or partially changed. Then simulation results are given.

Key words: model reference adaptive identification; rotor speed estimation; stator flux identification
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感应电动机直接转矩控制系统的模型参考自适应辨识

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摘要:首先提出一种基于感应电动机直接转矩控制系统的定子磁通自适应辨识方案,在此基础上,提出电磁转矩的计算方法.最后给出一种转速实时自适应辨识方案,并分别讨论了感应电动机参数不变和部分参数变化时转子转速的动态辨识.仿真试验证明所提出方案是比较先进的.

关键词:模型参考自适应辨识;转子转速辨识;定子磁通辨识

1 Introduction

Compared with vector control, induction motor direct torque control system has some distinctive features, such as simple control algorithm, quick torque response, only one motor parameter requirement and so on[1]. But one of its drawbacks is imprecise stator flux estimation due to time-varying stator resistance, which results in low control performance[2]. An approach to solve this problem is to estimate stator resistance and then stator flux[2,3]. As an indirect estimation method, it can't identify stator flux adaptively. Moreover, Lunbeger observer and intelligent identifier are employed to get stator flux[4]. When highly precise rotor speed based on direct torque control is not needed[3], cost will increase if speed sensor is used, so the research on dynamic speed identification should be done. Two identifiers proposed in this paper can use obtainable information fully, which leads to quick convergence of the identifiers.

2 Model reference adaptive identification of stator flux

2.1 Reference model

Considering the following reference model[4]:

$$\begin{cases} \dot{X} = AX + BU, \\ Y = DX, \end{cases} \tag{1}$$

where

$$A = \begin{bmatrix} -\frac{1}{\sigma}(R_1+\frac{L_s}{L_r}R_2) & -\omega & \frac{R_2}{\sigma L_r} & \frac{\omega}{\sigma} \\ \omega & -\frac{1}{\sigma}(R_1+\frac{L_s}{L_r}R_2) & -\frac{\omega}{\sigma} & \frac{R_2}{\sigma L_r} \\ -R_1 & 0 & 0 & 0 \\ 0 & -R_1 & 0 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} \frac{1}{\sigma} & 0 & 1 & 0 \\ 0 & \frac{1}{\sigma} & 0 & 1 \end{bmatrix}^{\mathrm{T}}, \quad D = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

$$\sigma = \frac{L_s L_r - L_m^2}{L_r} > 0,$$

$$X = (i_{\alpha 1}, i_{\beta 1}, \varphi_{\alpha 1}, \varphi_{\beta 1})^{\mathrm{T}}, \quad U = (u_{\alpha 1}, u_{\beta 1})^{\mathrm{T}},$$

where $i_{\alpha 1}, i_{\beta 1}, \varphi_{\alpha 1}, \varphi_{\beta 1}, u_{\alpha 1}, u_{\beta 1}$ denote the components of stator current, stator flux and stator voltage aligned wi-

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th α,β axis of stationary co-ordinates. L_s and L_r are stator and rotor self inductance respectively. L_m is mutual inductance between stator and rotor, ω is rotor angular speed, R_1, R_2 are stator and rotor resistance respectively.

2.2 Stator flux adaptive identification

Adaptive identification model is chosen as:

$$\begin{cases}\dot{\hat{X}} = \hat{A}X_1 + BU + G(\hat{Y} - Y),\\ \hat{Y} = D\hat{X},\end{cases} \tag{2}$$

where state $\hat{X} = (\hat{i}_{\alpha1}, \hat{i}_{\beta1}, \hat{\varphi}_{\alpha1}, \hat{\varphi}_{\beta1})^{\mathrm{T}}$ are estimated values of $i_{\alpha1}, i_{\beta1}$ and $\varphi_{\alpha1}, \varphi_{\beta1}$, $X_1 = (i_{\alpha1}, i_{\beta1}, \hat{\varphi}_{\alpha1}, \hat{\varphi}_{\beta1})$, $G = \begin{bmatrix} g_{11} & g_{21} & g_{31} & g_{41} \\ g_{12} & g_{22} & g_{32} & g_{42}\end{bmatrix}^{\mathrm{T}}$. Substituting time-varying parameters $\hat{R}_1, \hat{R}_2, \hat{\omega}$ for time-invariant R_1, R_2, ω in matrix A, we can get matrix $\hat{A}$. Hence, error model satisfies the following form:

$$\begin{cases}\dot{e} = Se + b\bar{\omega}\phi,\\ e_1 = Ee,\end{cases} \tag{3}$$

where

$$S = \begin{bmatrix} g_{11} & g_{12} & \dfrac{R_2}{\sigma L_r} & \dfrac{\omega}{\sigma} \\ g_{21} & g_{22} & \dfrac{-\omega}{\sigma} & \dfrac{R_2}{\sigma L_r} \\ g_{31} & g_{32} & 0 & 0 \\ g_{41} & g_{42} & 0 & 0, \end{bmatrix},$$

$$\bar{\omega} = \begin{bmatrix} -\dfrac{i_{\alpha1}}{\sigma} & -\dfrac{L_s i_{\alpha1}}{\sigma L_r} + \dfrac{\hat{\varphi}_{\alpha1}}{\sigma L_r} & \dfrac{\hat{\varphi}_{\beta1}}{\sigma} - i_{\beta1} \\ -\dfrac{i_{\beta1}}{\sigma} & -\dfrac{L_s i_{\beta1}}{\sigma L_r} + \dfrac{\hat{\varphi}_{\beta1}}{\sigma L_r} & -\dfrac{\hat{\varphi}_{\alpha1}}{\sigma} + i_{\alpha1} \\ -i_{\alpha1} & 0 & 0 \\ -i_{\beta1} & 0 & 0 \end{bmatrix},$$

$$e = [\hat{i}_{\alpha1} - i_{\alpha1}, \hat{i}_{\beta1} - i_{\beta1}, \hat{\varphi}_{\alpha1} - \varphi_{\alpha1}, \hat{\varphi}_{\beta1} - \varphi_{\beta1}]^{\mathrm{T}},$$

$$\phi = [\hat{R}_1 - R_1, \hat{R}_2 - R_2, \hat{\omega} - \omega)]^{\mathrm{T}}.$$

b, E are 4×4 identity matrix.

Conclusion 1 If matrix G satisfies $S^{\mathrm{T}} + S \leqslant 0$ and adaptive law is $\dot{\phi} = -R^{-1}\bar{\omega}^{\mathrm{T}}b^{\mathrm{T}}e$, error model will converge.

Proof Let a candidate for the Lyapunov function to be given by

$$v = e^{\mathrm{T}}e + \phi^{\mathrm{T}}R\phi, \tag{4}$$

where R is a symmetric positive-definite matrix. Taking time derivative of v along trajectory Eq. (3) and rearranging, we can get

$$\dot{v} = e^{\mathrm{T}}(S^{\mathrm{T}} + S)e + 2\dot{\phi}^{\mathrm{T}}R\phi + 2e^{\mathrm{T}}b\bar{\omega}\phi.$$

When adaptive law is chosen as $\dot{\phi} = -R^{-1}\bar{\omega}^{\mathrm{T}}b^{\mathrm{T}}e$ and matrix G can make $(S^{\mathrm{T}} + S) \leqslant 0$, then $\dot{v} \leqslant 0$. By the stability theorem of Lyapunov, this error model is stable asymptotically. So we can draw two conclusions:

1) $e, e_1, \phi, v \in L_\infty$;

2) $e, e_1 \in L_2$, $\dot{e} \in L_\infty$.

Considering the corollary of Barbalet theorem and the actual case of induction motor, there exist $e \to 0$ and $\phi \to 0$ when frequency component of $\bar{\omega}$ is full enough and $t \to \infty$. We know that $(S^{\mathrm{T}} + S)$ is 4×4 symmetric matrix, according to the definition of negative definite matrix, the value range of matrix G is:

1) $g_{11} < 0$;

2) $g_{22} < 0$;

3) $-2\sqrt{g_{11}g_{22}} \leqslant g_{12} + g_{21} \leqslant 2\sqrt{g_{11}g_{22}}$;

4) $g_{31} = -\dfrac{R_2}{\sigma L_r} = -\dfrac{\hat{R}_2 - e_{R_2}}{\sigma L_r}$, $g_{32} = \dfrac{\omega}{\sigma} = \dfrac{\hat{\omega} - e_\omega}{\sigma}$;

5) g_{41}, g_{42} can be any real value.

It can be seen from $\dot{\phi} = -R^{-1}\bar{\omega}^{\mathrm{T}}b^{\mathrm{T}}e$ that adaptive law of stator resistance is dependent on state error of stator flux, which can not be known directly. From the adaptive law and Eq. (3), we have:

$$\dot{e}_{R_1} = -\frac{1}{\sigma}i_{\alpha1}e_{i_{\alpha1}} - \frac{1}{\sigma}i_{\beta1}e_{i_{\beta1}} - i_{\alpha1}e_{\varphi_{\alpha1}} - i_{\beta1}e_{\varphi_{\beta1}}, \tag{5}$$

$$\dot{e}_{\varphi_{\alpha1}} = g_{31}e_{i_{\alpha1}} - e_{R_1}i_{\alpha1}, \tag{6}$$

$$\dot{e}_{\varphi_{\beta1}} = g_{42}e_{i_{\beta1}} - e_{R_1}i_{\beta1}. \tag{7}$$

Then error of stator flux can be reconstructed in Fig. 1. Fig. 2 presents adaptive identification principle of stator flux.

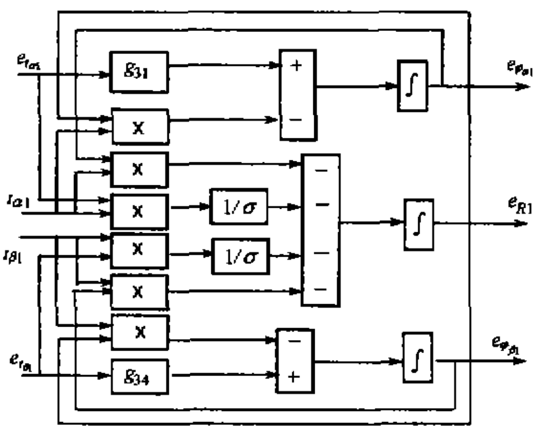

Fig. 1 Reconstruction of stator flux

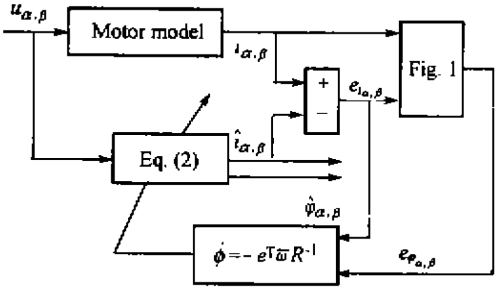

Fig. 2 Adaptive identification structure of stator flux

3 Electromagnetic torque estimation

Torque can not be known by measurement but estimation. By the above adaptive identification, stator flux converges to its true value quickly when torque is not known. Hence, torque estimation is

$$t_e = 1.5n_p(\hat{\varphi}_{\alpha 1} i_{\beta 1} - \hat{\varphi}_{\beta 1} i_{\alpha 1}). \tag{8}$$

4 Rotor speed model reference adaptive identification

In Section 2, rotor speed is identified as an unknown parameter. Now, we discuss another identification approach of rotor speed, which is of fast convergence.

4.1 Stator current reference model

Stator current and flux models are given in Eqs. (9) and (10)[4]:

$$\begin{aligned}
\dot{i}_{\alpha 1} &= -\frac{R_1}{\sigma} i_{\alpha 1} + \frac{\omega L_m^2}{\sigma L_r} i_{\beta 1} + \frac{L_m R_2}{\sigma L_r} i_{\alpha 2} + \frac{L_m}{\sigma}\omega i_{\beta 2} + \frac{1}{\sigma} u_{\alpha 1},\\
\dot{i}_{\beta 1} &= -\frac{\omega L_m^2}{\sigma L_r} i_{\alpha 1} - \frac{R_1}{\sigma} i_{\beta 1} + \frac{L_m}{\sigma}\omega i_{\beta 2} + \frac{L_m R_2}{\sigma L_r} i_{\beta 2} + \frac{1}{\sigma} u_{\beta 1},
\end{aligned} \tag{9}$$

$$\begin{aligned}
\varphi_{\alpha 1} &= L_s i_{\alpha 1} + L_m i_{\alpha 2},\\
\varphi_{\beta 1} &= L_s i_{\beta 1} + L_m i_{\beta 2},
\end{aligned} \tag{10}$$

where $i_{\alpha 2}, i_{\beta 2}$ are rotor current components with respect to stationary frame α, β. Substituting Eq. (10) into Eq. (9), Eq. (9) can be rearranged as

$$\begin{cases} \dot{X} = AX + BV, \\ Y = EX, \end{cases} \tag{11}$$

where

$$A = \begin{bmatrix} -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) & -\omega \\ \omega & -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) \end{bmatrix},$$

$$B = \frac{1}{\sigma}\begin{bmatrix} 1 & 0 & \frac{1}{T_2} & \omega \\ 0 & 1 & -\omega & \frac{1}{T_2} \end{bmatrix},$$

$$E = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\ X = [i_{\alpha 1}, i_{\beta 1}]^{\mathrm{T}},$$

$$V = (u_{\alpha 1}, u_{\beta 1}, \varphi_{\alpha 1}, \varphi_{\beta 1})^{\mathrm{T}},\ T_2 = \frac{L_r}{R_2}.$$

4.2 The parameters of induction motor are constant

Assuming that motor parameters are constant, stator flux can be estimated by $\varphi = \int (U - R_1 i_1)\mathrm{d}t$. To use measurable signal fully, estimation model can be chosen as

$$\begin{cases} \dot{\hat{X}} = C\hat{X} + (\hat{A} - C)X + \hat{B}U + K(\hat{Y} - Y), \\ \hat{Y} = E\hat{X}, \end{cases} \tag{12}$$

where $\hat{X} = [\hat{i}_{\alpha 1}, \hat{i}_{\beta 1}]^{\mathrm{T}}$, $\hat{\omega}$ is the estimated rotor speed, U and other variables have the same meaning as before.

$$\hat{A} = \begin{bmatrix} -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) & -\hat{\omega} \\ \hat{\omega} & -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) \end{bmatrix},$$

$$\hat{B} = \frac{1}{\sigma}\begin{bmatrix} 1 & 0 & \frac{1}{T_2} & \hat{\omega} \\ 0 & 1 & -\hat{\omega} & \frac{1}{T_2} \end{bmatrix},\ K = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix},$$

$$\hat{C} = \begin{bmatrix} -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) & 0 \\ 0 & -\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) \end{bmatrix}.$$

Hence, error model can be described as

$$\begin{cases} \dot{e} = (C + K)e + b\phi\bar{\omega}, \\ e_1 = Ee, \end{cases} \tag{13}$$

where $e = (\hat{i}_{\alpha 1} - i_{\alpha 1}, \hat{i}_{\beta 1} - i_{\beta 1})^{\mathrm{T}}$, $\phi = \hat{\omega} - \omega$, $\bar{\omega} = \left[\frac{1}{\sigma}\varphi_{\beta 1} - i_{\beta 1} \quad -\frac{1}{\sigma}\varphi_{\alpha 1} + i_{\alpha 1}\right]^{\mathrm{T}}$, $b = E$.

Conclusion 2 When matrix K satisfies $(C + K) + (C + K)^{\mathrm{T}} \leqslant 0$ and $\dot{e}_{\omega}(t) = -\frac{1}{r}\bar{\omega}^{\mathrm{T}} K^{\mathrm{T}} b^{\mathrm{T}} e(t)$, error model will converge asymptotically.

Proof $(C + K) + (C + K)^{\mathrm{T}}$ is 2×2 symmetrical matrix, by definition of negative definite matrix, we can get

$$k_{11} < \frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}),$$

$$k_{22} < \frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}),$$

$$(k_{12} + k_{21})^2 \leqslant [-\frac{2}{\sigma}(R_1 + \frac{L_s}{T_2}) + 2k_{11}][-\frac{1}{\sigma}(R_1 + \frac{L_s}{T_2}) + 2k_{22}].$$

Lyapunov function is defined as

$$v = e^{\mathrm{T}}(t)Pe(t) + r\phi^{\mathrm{T}}(t)\phi(t),$$

where $r > 0$, the time derivative of v is

$$\dot{v} = -e^{\mathrm{T}}(t)Qe(t) + e^{\mathrm{T}}(t)Pb\bar{\omega} + \bar{\omega}^{\mathrm{T}} b^{\mathrm{T}} Pe(t) + 2r\dot{\phi}. \tag{14}$$

When $e^{\mathrm{T}}(t)Pb\phi\bar{\omega} + \bar{\omega}^{\mathrm{T}}\phi^{\mathrm{T}} b^{\mathrm{T}} Pe(t) + 2r\dot{\phi} = 0$, then $\dot{v} = -e^{\mathrm{T}}(t)Qe(t) \leqslant 0$. It means that error model is stable asymptotically. Since $e^{\mathrm{T}}(t)Pb\,\bar{\omega} = \bar{\omega}^{\mathrm{T}}b^{\mathrm{T}}Pe(t)$, so $\dot{e}_\omega(t) = -\frac{1}{r}\bar{\omega}^{\mathrm{T}}b^{\mathrm{T}}Pe(t)$. Hence we can conclude $e(t) \in L_\infty, \phi \in L_\infty, \dot{e}(t) \in L_\infty, v(t) \in L_\infty$.

By using similar argument as in Section 2, it can be shown that $e(t) \to 0$ and $\phi \to 0$ when $t \to \infty$.

4.3 Some parameters are slow time-varying

It can be seen that both of Eqs. (11) and (12) are dependent on parameters of induction motor. In fact, these parameters are time-varying. Assuming that staor flux is obtained with no relation to speed and resistance (such as fuzzy neural network[4]) and converges quickly, estimation model is chisen as:

$$\begin{cases} \dot{\hat{X}} = \hat{C}\hat{X} + (\hat{A} - \hat{C})X + \hat{B}V + K(\hat{Y} - Y), \\ \hat{Y} = E\hat{X}, \end{cases} \tag{15}$$

where

$$\hat{A} = \begin{bmatrix} -\frac{1}{\sigma}(\hat{R}_1 + \frac{L_s}{L_r}\hat{R}_2) & -\hat{\omega} \\ \hat{\omega} & -\frac{1}{\sigma}(\hat{R}_1 + \frac{L_s}{L_r}\hat{R}_2) \end{bmatrix},$$

$$\hat{B} = \frac{1}{\sigma}\begin{bmatrix} 1 & 0 & \frac{\hat{R}_2}{L_r} & \hat{\omega} \\ 0 & 1 & -\hat{\omega} & \frac{\hat{R}_2}{L_r} \end{bmatrix},$$

$$\hat{C} = \begin{bmatrix} -\frac{1}{\sigma}(\hat{R}_1 + \frac{L_s}{L_r}\hat{R}_2) & 0 \\ 0 & -\frac{1}{\sigma}(\hat{R}_1 + \frac{L_s}{L_r}\hat{R}_2) \end{bmatrix}.$$

Using Eq. (15) minus Eq. (11), error model can be derived as:

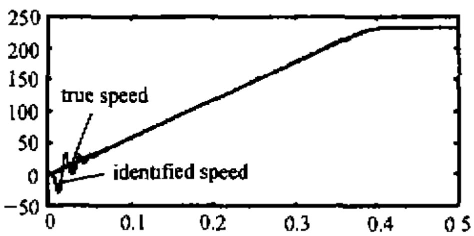

Fig. 3 Rotor speed for time-varying parameter

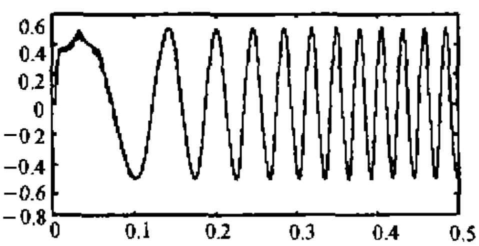
Fig. 5 β phase flux

$$\begin{cases} \dot{e}(t) = (C + K)e(t) + b(\phi\bar{\omega})^T, \\ e_1(t) = Ee(t), \end{cases} \tag{16}$$

where

$$\phi = [e_{R1} \quad e_{R2} \quad e_\omega],$$

$$\bar{\omega} = \begin{bmatrix} -\frac{1}{\sigma}\hat{i}_{\alpha 1} & -\frac{L_s}{\sigma L_r}\hat{i}_{\alpha 1} + \frac{1}{\sigma L_r}\varphi_{\alpha 1} & -i_{\beta 1} + \frac{1}{\sigma}\varphi_{\beta 1} \\ -\frac{1}{\sigma}\hat{i}_{\beta 1} & -\frac{L_s}{\sigma L_r}\hat{i}_{\beta 1} + \frac{1}{\sigma L_r}\varphi_{\beta 1} & i_{\alpha 1} - \frac{1}{\sigma}\varphi_{\alpha 1} \end{bmatrix}^{\mathrm{T}}.$$

Similar to Conclusion 2, the value range of matrix K can be obtained, here, the proof procedure is omitted.

Conclusion 3 If K satisfies $(C + K)^T + (C + K) \leqslant 0$ and $\dot{\phi} = -e^{\mathrm{T}}b\,\bar{\omega}^{\mathrm{T}}R^{-1}$, error model converges.

Proof Lyapunov function is given as

$$v = e^T(t)e(t) + \phi R\phi^{\mathrm{T}},$$

where R is a 3×3 symmetric positive definite matrix, with the same argument as Conclusion 2 and the space limitation, the adaptive law of parameters is omitted here.

5 Simulation

Simulation test is done with dynamical simulation tool Simulink 2.2. Provided that stator resistance and rotor resistance varies in proportion to time, we can get dynamical identification of rotor speed in Fig. 3, it can be seen that speed converges quickly. Figs. 4, 5 and 6 demonstrate the simulation result of stator flux and toque under the same assumption. Using the actual stator current during the identification, stator flux and torque converge quickly. (Note: dash curve and real curve represent identified and true value respectively in Figs. 4 and 5).

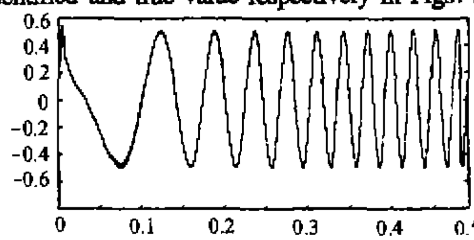
Fig. 4 α plase flux

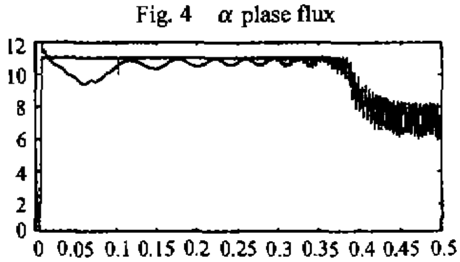
Fig. 6 Electromagnetic torque

(Continued on page 914)

$$\dot{V} = -q(\lambda^2 v^2 + w^2) + (pC_p + qC_q)(x^2 + y^2)^2 + \cdots, \tag{20}$$

where the ellipses denote infinitely small terms whose orders are higher than the fourth.

So the particular solution in equation (3) is asymptotically stable. This shows that the problem of passive stabilization about oscillating of body S is solved by introducing supplementary degree of freedom which is determined by coodinate u (namely block s is defrozen).

Remark We point out that if we use a geostationary satellite to take a picture of a certain object on the ground, it is very important for the camera to take aim, namely the motion of the satellite must be asymptotically stable. Usually, the effect brought by a small pertubation is removed by the reaction of a jet stream, which is produced by burning fuel, but the astronautic fuel is very expensive (Fig.2, Fig.3 in the paper [2]). The result obtained by us shows that the satellite can also be stabilized by means of the relative motion of some piece of the satellite moving in a nonideal fluid as an oscillator with damping and this does not require additional energy.

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6 Conclusion

Two dynamical identification schemes of stator flux and rotor speed proposed in this paper are based on special model reference adaptive principle, both of them use obtainable information fully. According to Lyapunov stability theorem, adaptive laws of parameters are synthesized to make state and parameters converge quickly even the parameter variant laws are not sure. Simulation shows their advance.

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