Robust Indirect Adaptive Control Using RLS for DC Motor

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Abstract

Recently, the DC motor has been widely used in industry even though its maintenance costs are higher than the induction motor. Sometimes the conventional feedback control cannot work well to cope with the changes that vary in its dynamic system. The parameters of the dynamic system that changes with time lead to a conventional feedback control system is not able to maintain control. This is caused by circumstances which are nonlinear and receive many disturbance so that the transient response of the system to be less precise and accurate to the desired steady state conditions. To overcome these problems, this paper presents an indirect adaptive control system which can cope with the change of the dynamic DC motor system. The adaptive control scheme comprises a recursive least square (RLS) parameter identification and robust control method. A robustifying control term is added to accommodate the approximation errors and disturbance. This makes the algorithm robust to changes in the plant. Simulation results prove the effectiveness of the controller.

Keywords: DC motor, time varying, indirect adaptive control, robust control, RLS.

1. Introduction

The brushed DC motor is widely used in many variable speed drives. Open-loop operation of the motor can be unsatisfactory in some industrial applications. If the drive requires constant-speed operation under changing load torque, closed-loop control is necessary. The dynamic response of the brushed dc motor angular velocity control depends on the designed control law.

A high performance motor drive system must have good dynamic responses, although the motor parameters are time varying. The development of new technologies for dc motor control such as PID, optimal, robust, and other control laws have been proposed in many applications (Chow and Tipsuwan, 2003; Delibasi et.al., 2004; Dobra, 2002; Gurbuz, 1999; Kucukdemiral et.al., 1999; Ohm, and Oleksuk, 2002; Sevinc, 2003). Generally, these high performance control laws depend on the operation conditions. In high performance drive, adaptive control is the best control law if parameters of system to be controlled are time varying (Astrom and Wittenmark, 1995). Angular velocity control of brushed DC motor is time varying system, hence adaptive control is one of the best controller.

Adaptive control is a label assigned to a wide group of approaches, which are based on variations of the control inputs adequately to a priori unknown variations of the plant's dynamics (Craig et.al., 1987). There are two widely distinct approaches of adaptive control: direct and indirect ones (Betechuoh et.al., 2007). In direct adaptive control, the parameters defining the controller rather than describing the system itself are updated directly, while indirect adaptive control relies on on-line identification of plant parameters with an assumption that a suitable controller is implemented.

The traditional adaptive system may go unstable in the presence of small disturbances (Ioannou and Sun, 1996). We use standard gradient descent to estimate on-line the plant dynamics. The control law is synthesized based on these estimates and a robustifying control term is added to cancel out the effect of approximation errors and disturbance.

This paper proposes a high performance robust indirect adaptive control law for controlling the brushed dc motor angular velocity. This method should be able to learn about parameters changes by processing the output of system and use appropriate controller to accommodate them so it avoids the need of the knowledge the mechanical parameters of motor exactly (Astrom and Wittenmark, 1995). It is proposed the application of this technique on the mechanic part of the system.

2. Modeling

We adopt from (Kucukdemiral et.al., 1999) for the nominal first order linear model of a motor is shown in (15).

$$\frac{d\omega}{dt} + 2\omega = 50.3\, V_t - \frac{T_L}{19.8 \times 10^{-6}} \tag{1}$$

Since T_L is unknown, it can be included in the plant perturbation, hence transfer function of the nominal plant is

$$G_0(s) = \frac{50.3}{s+2} \tag{2}$$

The exact model and the nominal model can be related as

$$G = G_0(1 + \Delta_m) \tag{3}$$

where G is exact model, G_0 is nominal model, and Δ_m is a multiplicative perturbation.

3. Indirect adaptive control

Adaptive methods seek to use on-line observations, as well as a priori information, to improve the control of system over time in response to changes and unknowns in the system and environment (Astrom and Wittenmark, 1995). Adaptive methods in control system posses several advantages, e.g., fast response, good transient response, robustness of stability, insensitivity to the matching parameters variations and external disturbances. Indirect Adaptive Control (IAC) is one of adaptive model methods.

The control system architecture is shown in Fig. 1. It can be seen that an explicit separation between identification and control is assumed. The basic idea is that a suitable controller can be designed on line if a model of the plant is estimated on line from the available input-output measurements. The scheme is termed indirect because the adaptation of the controller parameters is done in two stages: (1) on-line identification of the plant parameters; (2) on-line computation of the controller parameters based on the current identified plant model.

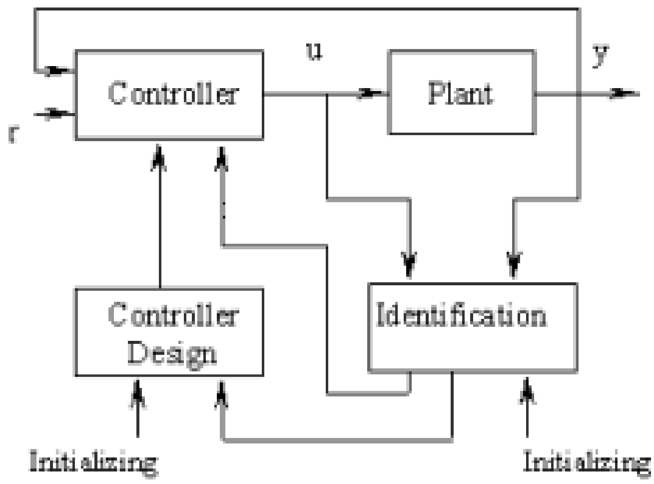

Fig. 1: The scheme of indirect adaptive control

The identification process consists of estimating the unknown parameters of the system dynamics (Ljung, 1987). The recursive least square (RLS) method has been recommended for the identification process for easy implementation and application to real systems.

Recursive least squares (RLS) methods that have been widely used with several advantages such as easy numerical solution and fast parameter convergence gives a consistent modelling accuracy over a wide range of operating conditions and is the best linear unbiased estimate (Soderstrom and Stoica, 1989; Ljung and Glad, 1994).

The discrete mathematical model of the DC motor can be described in terms of input u(t) and output y(t) with the adequate order of the coefficients A, B as:

$$Ay(t) = Bu(t-1) \tag{4}$$

where u(t) is discrete input signal, y(t) is discrete output signal, and

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_n z^{-n} \tag{5}$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_m z^{-m} \tag{6}$$

A model of the system (4) can be presented in the form of

$$y(t) = x^T \theta \tag{7}$$

where is a vector of unknown parameters defined by

$$\theta^T = [-a_1, \cdots, -a_n, b_0, \cdots, -a_m] \tag{8}$$

and θ , vector of regression which consists of measured values of input and output

$$\begin{aligned} x^T(t) = [&y(t-1), \cdots, y(t-n), \\ &u(t-1), \cdots, u(t-m-1)] \end{aligned} \tag{9}$$

A model given with (7) presents an accurate description of the system. However, in this expression the vector of system parameters θ is not known. It is important to determine it by using available data in signal samples at system output and input. For that purpose a model of a system is supposed

$$y(t) = x^T \hat{\theta} + \hat{e}(t) \tag{10}$$

where $\hat{\theta}$ is a vector of supposed values of system parameters, and $\hat{e}(t)$ is an error in modeling at the moment t.

The vector of supposed values of the parameters, $\hat{\theta}$, should be chosen in such a way that the whole error in modeling can be minimized. From (7) and (10) it appears that

$$\hat{e}(t) = x^T(\theta - \hat{\theta}) \tag{11}$$

After the time interval of N sampling periods, a model (10) can be shown in a vector form

$$\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(N) \end{bmatrix} = \begin{bmatrix} \mathbf{x}^T(1) \\ \mathbf{x}^T(2) \\ \vdots \\ \mathbf{x}^T(N) \end{bmatrix} \hat{\boldsymbol{\theta}} + \begin{bmatrix} \hat{e}(1) \\ \hat{e}(2) \\ \vdots \\ \hat{e}(N) \end{bmatrix} \tag{12}$$

By choosing an adequate performance function (Robertson and Lee, 2002), based on the square prediction error:

$$J = \sum_{1}^{N} \hat{e}^2 = \hat{e}^T \hat{e} \tag{13}$$

the unknown parameters of the system are determined as a solution to:

$$\frac{\partial J}{\partial \hat{\theta}} = 0 \tag{14}$$

According to (12) and (13), the solution of the equation (14) has a form

$$\hat{\theta} = \left[x^T x\right]^{-1}\left[x^T y\right] \tag{15}$$

Sometimes, the assessment is needed to be done whenever the information is coming about input/output samples, that is, in each sampling period. The technique which is appropriate for this purpose is Recursive Least Squares Method. With this method, a supposed model from the previous sampling period $\hat{\theta}(t-1)$ is used for assessment of $\hat{y}(t)$ system output in the given sampling period. Estimated system output is compared with the real system output y(t) and on the basis of the obtained difference an error signal ε(t) is generated. Now, so called mechanism of updating, on the basis of error signal, correct values of supposed parameters of the system $\hat{\theta}(t-1)$ on $\hat{\theta}(t)$. Scheme of the recursive estimation is given in Fig. 2.

If the following symbols are introduced

$$P(t) = \left[x^T(t)x(t)\right]^{-1} \tag{16}$$

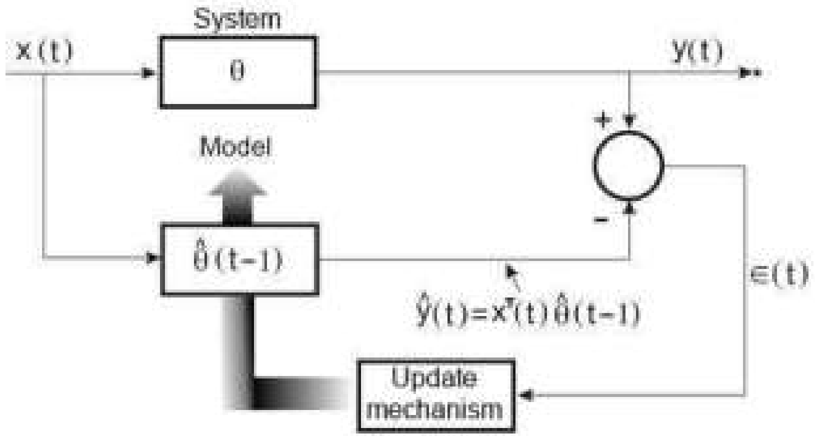

Fig. 2: Scheme of recursive least squares method

Suppose now that the DC motor parameters are identified on a a short time (eg starting). the used algorithm to identify the mechanical and electrical parameters is based on the recursive least squares:

$$\begin{aligned} \hat{\theta}(k) &= \hat{\theta}(k-1) + L(k)\varepsilon(k) \\ \varepsilon(k) &= y(k) - \Phi^T(k)\hat{\theta}(k-1) \\ L(k) &= \frac{P(k-1)\Phi(k)}{1+\Phi^T(k)P(k-1)\Phi(k)} \\ P(k) &= P(k-1) - \frac{P(k-1)\Phi(k)\Phi^T(k)P(k-1)}{1+\Phi^T(k)P(k-1)\Phi(k)} \end{aligned} \tag{17}$$

Accordingly, transfer function of the observed system is in the form of

$$G_p(z) = \frac{\alpha}{1-\beta z^{-1}} \tag{18}$$

Use the backward difference transformation of (18)

$$s = \frac{1-q^{-1}}{h} \tag{19}$$

The continuous parameters are found via the relations

$$\begin{pmatrix} a \\ b \end{pmatrix} = \frac{1}{h}\begin{pmatrix} 1-\alpha \\ \beta \end{pmatrix} \tag{20}$$

where h is sampling period.

The dynamic equation of a motor can be approximated by using the following first order differential equation

$$\frac{d\omega}{dt} = -a\,\omega + b\,u \tag{21}$$

where $u = V_t$.

The objective of this paper is to design a control law $u(t)$ such that, the output, $\omega(t)$, will follow a desired trajectory, $\omega_d(t)$.

Let us define the tracking error as

$$e = \omega_d - \omega \tag{22}$$

Define also an error metric as

$$\sigma = e + \lambda \int_0^t e\, d\tau \tag{23}$$

where λ is a positive scalar. Note that the choice of the metric surface, $\sigma = 0$, guarantees that the tracking error, e, is governed after such finite amount of time by the first-order differential equation $\dot{e} + \lambda e = 0$. In case of ideal error metric motion the error metric and its phase velocities should be identically zero i.e.

$$\sigma = 0 \tag{24}$$

$$\dot{\sigma} = 0 \tag{25}$$

The necessary control input can be found as

$$u = \frac{1}{b}(\dot{\omega}_d + a\,\omega + \lambda\, e) \tag{26}$$

Since a and b, are unknown, so we propose the use of the following control law

$$u = \frac{1}{b_m}(\dot{\omega}_d + a_m \omega + u_m + \lambda\, e) + u_r \tag{27}$$

where u_r is a robustifying control term. In this paper we assume that $b_m \geq 0.1$.

he robustifying control term u_r can be constructed as a function of error metric, σ, as follow

$$u_r = w\,\sigma \tag{28}$$

The weight w is adaptable that is updated during the operation. The goal is to push σ to zero in finite time. To achieve this requirement, the following Lyapunov function is selected

$$V = \frac{1}{2}\sigma^2 \tag{29}$$

The function selected is positive definite and it vanishes only when $\sigma = 0$. A global reaching condition is its time derivative be negative definite. Choosing its time derivative as

$$\dot{V} = -\gamma \sigma^2 \quad (30)$$

where, γ is a positive constant, restricts the derivative to be negative definite. Substituting (29) into (30), the following equation is obtained

$$\dot{\sigma}\sigma = -\gamma \sigma^2 \quad (31)$$

Going one step further,

$$\sigma(\dot{\sigma} + \gamma \sigma) = 0 \quad (32)$$

Hence, for the Lyapunov stability criteria to be held,

$$\dot{\sigma} + \gamma \sigma = 0 \quad (33)$$

must be satisfied for $\sigma \neq 0$. The goal is to push the function $\dot{\sigma} + \gamma \sigma$ to zero. To achieve this goal the error function

$$E = \frac{1}{2}(\dot{\sigma} + \gamma \sigma)^2 \quad (34)$$

is introduced to the error metric function and the parameters are updated accordingly.

The parameters are updated using simple gradient descent approach –in continuous form– or back propagation :

$$\dot{\theta} = -\eta \frac{\partial E}{\partial \theta} \quad (35)$$

where, η is the learning constant, generally chosen between 0 and 1. To compute the parameter updates, the derivative of the error function E w.r.t. θ should be found. Using the chain rule, the derivative can be written as

$$\frac{\partial E}{\partial \theta} = \frac{\partial E}{\partial u}\frac{\partial u}{\partial \theta} \quad (36)$$

Substituting (33) into (36) and taking the derivatives, the following equations are obtained:

$$\begin{aligned} \frac{\partial E}{\partial \theta} &= (\dot{\sigma} + \gamma \sigma)\frac{\partial(\dot{\sigma} + \gamma \sigma)}{\partial u}\frac{\partial u}{\partial \theta} \\ \frac{\partial E}{\partial \theta} &= -k\,(\dot{\sigma} + \gamma \sigma)\frac{\partial u}{\partial \theta} \end{aligned} \quad (37)$$

As a result, the parameters update algorithm can be stated as

$$\dot{a}_m = \eta(\dot{\sigma} + \gamma \sigma)\omega \quad (38)$$

$$\dot{b}_m = -\eta\left(\frac{\dot{\sigma} + \gamma \sigma}{b_m}\right)(\dot{\omega}_d + a_m\omega + u_m + \lambda e) \quad (39)$$

$$\dot{u}_m = \eta(\dot{\sigma} + \gamma \sigma) \quad (40)$$

$$\dot{w} = \eta(\dot{\sigma} + \gamma \sigma)\sigma \quad (41)$$

4. Simulation results

Load torque is unknown but in the simulation it is assumed as follows.

$$T_L = 19.8 \times 10^{-6} \text{ Nm}$$

a. Assume that the values of the motor parameters are unknown

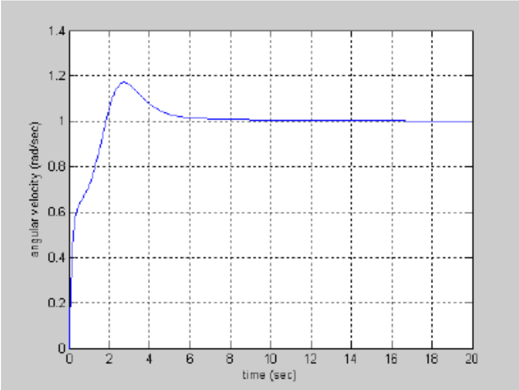

Fig. 3: Angular velocity transient response using controller with unknown parameters

b. Assume that the nominal values of the motor parameters are known

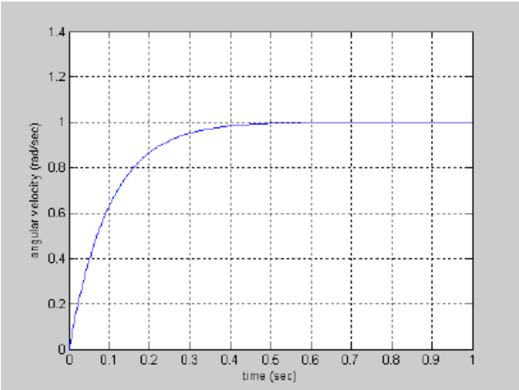

Fig. 4: Angular velocity transient response using controller with known parameters

Figure 3 shows angular velocity transient response if the motor parameters are unknown. The system is stable, but settling time is large enough, about 17 seconds. Figure **4** shows transient response after learning process to find exact parameters. Settling time is reduced, about 0.6 seconds. This facts show that control law using robust indirect adaptive control can control the angular velocity of brushed dc machine sufficiently without need to know the exact parameters. On the other hand, if the exact parameters are known then the performance of angular velocity control is better.

5. Conclusion

Actual experimentation on bulky power components can be expensive and time consuming. But simulation offers a fast and inexpensive means to learn more about these components.

The control law based on robust indirect adaptive control can control angular velocity of brushed dc motor, although the parameters of system are time varying. In order to increase the control system performance, the exact parameters are required.

The simulation and modeling of the DC motor also gave an inside look of the expected output when testing the actual DC motor. The results from the simulation were never likely to occur in real-life condition due to the response times and condition of the actual motor.

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