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Effects of State and Output Disturbance on the State Estimation for Speed Control Stochastic DC Motor

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Abstract: ***A speed control DC motor has been modeled from first principle and stochastic output obtained by simulation in MATLAB. Disturbances are injected randomly at each step input producing stochastic output. The output error was observed to follow Gaussian distribution hence Kalman filter was used to investigate the effect of the state and output disturbance on the estimate of DC motor state hence output. Simulation results show that increasing the DC motor state disturbance moves the estimated output close to the measured output. But increasing output disturbance moves the estimated state away from the measured state.***

Keywords: DC motor, speed control, Stochastic systems, Kalman filter

1. Introduction

DC motor is the most commonly used actuator in some industrial control systems and robotics. Due to its ability to move linearly and rotate, the DC motor can be used to provide output that can be angular position, velocity or acceleration. Figure 1 shows the electrical and mechanical components of a DC motor. It consists of the rotating armature called rotor on which is wound turns of coils. The stationary part called stator provides the magnetic field. The reverse holds for brushless DC motor where the rotor produces the field and the stator holds the coil [1]. Other configuration exists but this is the most common configuration.

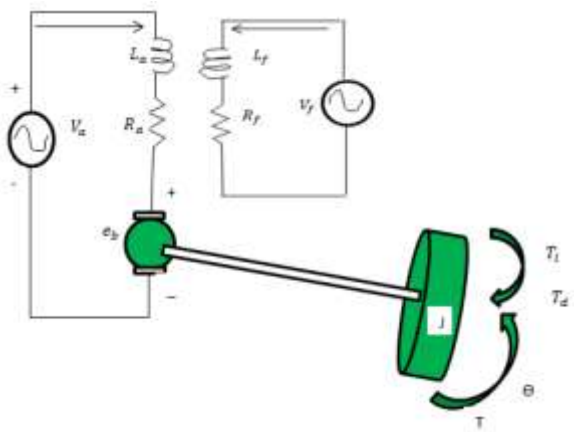

Figure 1: Free body diagrams for the electrical and mechanical parts of a DC motor

The DC motor is given a current necessary to create magnetic field for starting it up, a process called excitation. This can be separately-excited, where the excitation current is from an external source or self excited in which the DC motor supplies the excitation current. In separately-excited DC motor, the field current can be varied externally for flux control leading to variation of electrical constant hence stochastic output [2].

This paper presents a method for simulating DC motor subjected to varying load torque and measurement noise in MATLAB. The resulting stochastic speed output of the DC motor tracking error is examined. Thereafter, Kalman filter algorithm is formulated and used to estimate the output under different state disturbance and measurement noise.

2. Literature Review

The outputs of DC motor are assumed to be deterministic in nature but in actual case, the outputs are stochastic. This stochastic output results from varying load torque, sensor noise and error in motor parameter estimates[3]. This therefore makes the model less representative of the actual DC motor. If the effect of stochastic output is not accounted for during modeling, it can result in model which produces biased prediction hence difficult to control. The disturbance and noise input affect the state and the output respectively and are believed to follow Gaussian distribution [4]. Consequently, using the models obtained in this form pose problems for control system design.

To design controller for speed control of such DC motor involves different techniques starting from the modeling phase. One way is to use a model reference adaptive control (MRAC) [5] where the control law is designed to ensure that the plant output follows a given model even in the presence of parameter change or disturbances in the plant. Other apply a more intuitive and logical approach of stochastic model predictive control which determines the optimal control moves to apply to the DC motor in the presence of uncertainties [6, 7, 8]. The advantage of this approach is that the control moves can still perform satisfactorily even in the presence of up to 20 % model error [8]. But the setback of this approach is that it can be computationally demanding especially when DC motor model is obtained from step test.
Lyapunov stability criterion can be used to design optimal state feedback for the DC motor speed control if the states can be measured accurately [9]. The minimization of the Lyapunov function produces the optimal control input to the DC motor while the adaptive control provides the compensation for poor control performance resulting from

model error. But when a system state cannot be measured accurately, observer is used for state estimation for deterministic systems [10]. For stochastic systems, Kalman filter is used for state estimation hence output estimation. Kalman filter, an optimal state estimator is used to estimate the state of a system subjected to both process disturbance and output measurement noise. It does that by using prediction and update to obtain the estimate of the state from predicted state recursively [11, 12]. The Kalman gain forms part of the correction term for both the state and the covariance matrix.

3. Methodology

3.1 DC Motor Modeling

The force on a conductor within a magnetic field is given by equation 1 while the torque resulting from such force is given by equation 2. Equation 3 gives the torque for P number of turns while equation 4 is the back emf produced due to the rotating armature.

$$F = Bil \tag{1}$$

$$T = \Phi i \tag{2}$$

$$T = P\Phi i = k_1 i \tag{3}$$

$$E = k_2 \dot{\theta} \tag{4}$$

Applying Newton's second law of motion to the mechanical part gives equation 5.

$$J\ddot{\theta} = k_1 i - b\dot{\theta} - T_l \tag{5}$$

Applying Kirchoff's voltage law to the electrical part results in equation 6.

$$k_2\dot{\theta} + Ri + L\frac{di}{dt} = V_{in} \tag{6}$$

B is the flux density, i is the magnitude of the current flowing, l is the length of the conductor, Φ is the flux, k_1 is the torque constant and k_2 is the electrical constant [13].

To obtain the state space model of the DC motor taking angular position, angular speed and armature current as state variables, equations 5 and 6 are expressed as equations 7 and 8 respectively.

$$\ddot{\theta} = \frac{k_1}{J}i - \frac{b}{J}\dot{\theta} - \frac{1}{J}T_l \tag{7}$$

$$\frac{di}{dt} = {}^1/_L\,[u - k_2\dot{\theta} - Ri \tag{8}$$

Using equations (7) and (8) with the state variables as $[X_1 X_2 X_3]^T = [\theta\dot{\theta} i]^T$, implies

$$\begin{bmatrix} \dot{X}_1 \\ \dot{X}_2 \\ \dot{X}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & \frac{-b}{J} & \frac{K_1}{J} \\ 0 & \frac{-K_1}{L} & \frac{-R}{L} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L} \end{bmatrix} v_{in} - \begin{bmatrix} 0 \\ \frac{1}{J} \\ 0 \end{bmatrix} T_l \tag{9}$$

$$Y = [0\ 1\ 0] \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} + S \tag{10}$$

Equations 9 and 10 can be written in compact discrete form as equations 11 and 12.

$$x(k+1) = Ax(k) + Bu(k) + B_d u_d(k) \tag{11}$$

$$y = Cx(k+1) + S_d \tag{12}$$

The load torque T_l in equation 9 is the process disturbance input while S in equation 10 is the measurement noise both assumed to be Gaussian distributed with zero mean and a non zero variance.

3.2 Kalman Filter Algorithm

The algorithm for state estimation using Kalman filter is stated below where W and V are noise covariance for states and outputs respectively;

a) Assume an initial state estimate x(0)=x and initial covariance matrix P(0)=P.

b) Predict the next state $\hat{x}(k)$ and the next covariance matrix $\hat{P}$.

$$\hat{x}(k) = A\hat{x}(k-1) + Bu(k) \tag{13}$$

$$\hat{P}(k) = AP(k-1)A^T + W \tag{14}$$

(c) Compute the Kalman gain K.

$$K(k) = \frac{\hat{P}(k)C^T}{(C\hat{P}(k)C^T)+V} \tag{15}$$

(d) Take measurement of speed output y(k) and compute the predicted output. $\hat{y}(k)$

$$\hat{y}(k) = C\hat{x}(k) \tag{16}$$

(e) Update the prediction to next estimate

$$x(k) = \hat{x}(k) + K(k)\{y(k)-\hat{y}(k)\} \tag{17}$$

(f) Update the covariance matrix

$$P(k) = (I - K(k)C)\hat{P}(k) \tag{18}$$

Repeat the process until the Kalman gain minimizes the prediction error.

A is the state matrix of the DC motor, B is the input matrix and C is the output matrix.

The performance of this algorithm depends on both the context knowledge and the quality of measurement. When the context knowledge which leads to better prediction is better than measurement, the state estimate approaches the predicted state. On the other hand, if the measurement is better than the context knowledge, the prediction approaches the measurement.

3.3. Simulating Disturbance and Noise Input to the DC Motor

MATLAB is used to simulate the noise and disturbance input using the DC motor parameters given in table 1.

Table1: DC motor parameter values

Parameters	Symbols	values
Moment of inertia	J	2 Kgm^2/s
Friction coefficient	B	1 Js/rad
Torque constant	K_1	2 Vs/rad
Electrical constant	K_2	20 J/A
Resistance	R	10Ω
Inductance	L	0.5H

Putting Table 1 into equation 9 and 10 gives

$$\begin{bmatrix} \dot{X}_1 \\ \dot{X}_2 \\ \dot{X}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & -0.5 & 1 \\ 0 & -4 & -20 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix} v_{in} - \begin{bmatrix} 0 \\ 0.5 \\ 0 \end{bmatrix} T_l \tag{19}$$

Y=[0 1 0].

Equation 19 is the state space model of the DC motor. The load torque varies randomly with mean of 30 and the random noise has mean of 0 and variance 0.001. Simulating the step response 400 times, and taking steady state error, figure 2 is obtained. Figure 3a shows the resulting open loop DC motor with output noise and variable disturbance in the state while figure 3b shows the error that follows Gaussian distribution. The mesh plot of the tracking error to show the error in three dimensions produces a rough surface as shown in figure 2. This results from the stochastic nature of the output speed due to the combined effect of the varying load torque and the measurement noise. The orientation of the resulting error changes with values of the DC motor parameters. Figure 3a shows the rough step response as opposed to the smooth response that characterizes noiseless DC motor. Figure 3b shows that the noise effect follows Gaussian distribution with zero mean and given variance.

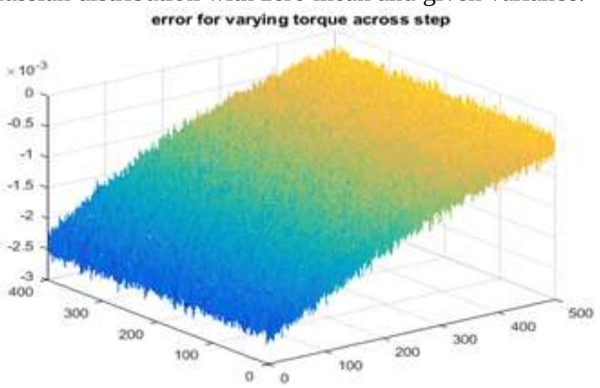

Figure 2: Tracking errors when load torque is randomly injected at each data set.

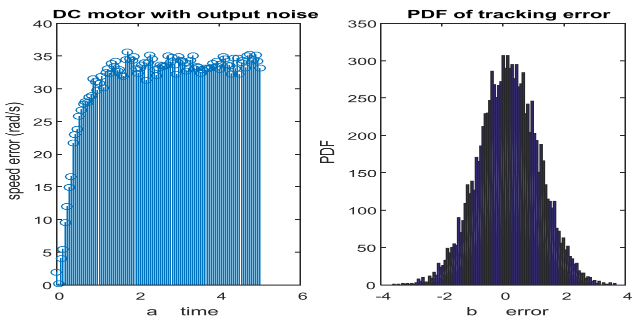

Figure 3: DC motor with output noise

Since the output to a step response for the DC motor is stochastic as shown by figure 2 and 3, The output can be estimated by using Kalman filter.

4. Effects of State and Output disturbance on Quality of Estimate

The state estimation is carried out by following the algorithms stated in section 3. The output matrix as shown in equation 19 implies the output is the speed of the DC motor. Figure 4 shows the DC motor measured and estimated outputs with state disturbance w=0.001 and measurement noise v=1. Figure 5 shows same but w=1000.

It can be seen from figures 4 and 5 that the Kalman filter estimated the speed output of the DC motor closely. Figure 4 with small value of state disturbance w, shows deviation of the estimated output from the measured output. Figure 5 with larger value of the state disturbance has estimated output more closely matching the measured output.

The state disturbance was kept at w=1 while the output disturbance v=0.001. Figure 6 shows the measured and the estimated outputs for the motor speed. Figure 7 shows estimated and measured output for v=1000.Figure 6 with a low value of measurement noise v has the estimated output more closely matching the measured output compared to figure 7 with higher measurement noise v.

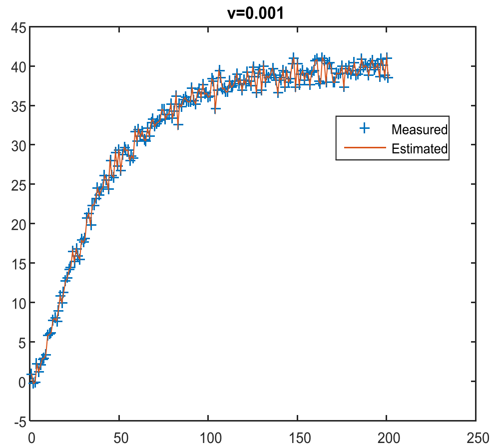

Figure 4: Measured and estimated speed for state disturbance w=0.001.

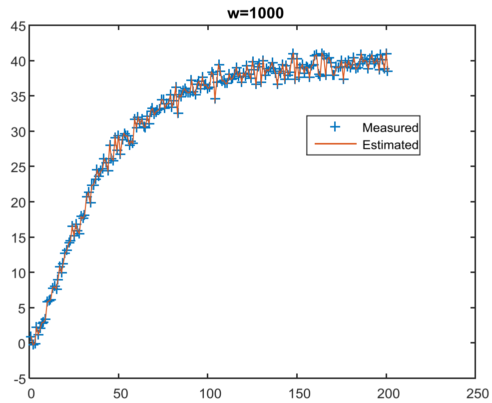

Figure 4: Measured and estimated speed for state disturbance w=1000

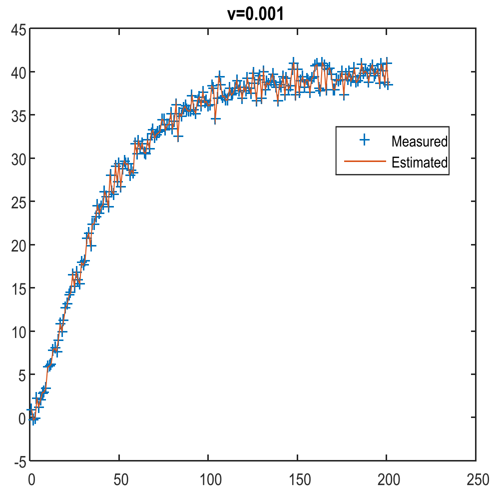

Figure 6: Measured and estimated speed for output disturbance v=0.001.

This is the reverse of figures 4 and 5 where the higher state disturbance produces estimated output that more closely matches the measured out.

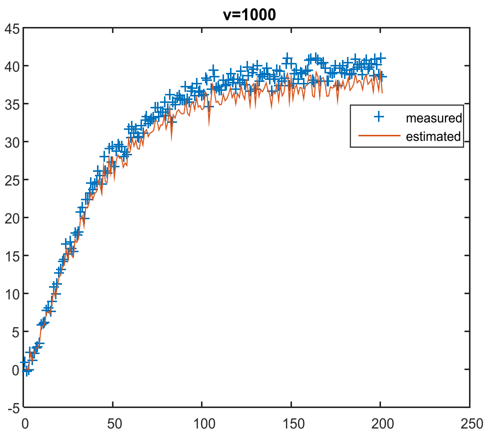

Figure 7: Measured and estimated speed for output disturbance v=1000.

5. Conclusion

The DC motor subjected to varying load torque and measurement noise has been modeled. The disturbances has been simulated in MATLAB and seen to follow Gaussian distribution. Estimating the states using Kalman filter provides two contrasting results. The estimated state approaches the measured state when the state disturbance is higher than when it is lower. On the other hand, the estimated state approaches measured state when the measurement noise is lower than when it is higher.

References

[1] A.A. Ahmed, A. Ali-Eldin, M.S. Elksasy, F.F. Areed, “Brushless DC Motor Speed Control using both PID Controller and Fuzzy Controller and Neo Fuzzy Controller,” International Journal of Computer Applications, 109 (10), pp. 47-52, (2015).

[2] N.D. Pandey, P. Tiwary, “Comparison between Speed Control DC Motor Using Genetic Algorithm and PSO-PID Algorithm,” International Journal of Electrical Engineering and Technology, 8 (1), pp. 17-25 (2017).

[3] M.R.Khan, A.A.Khan, U. Ghazali, “Speed Control of DC Motor Under varying Load Torque Using PID Controller,” International Journal of Engineering, 9(3), pp. 38-48, (2015).

[4] H. Wang, Bonded Dynamic Systems: Modeling and Control, Springer, London, 2000.

[5] G. Shahgholian, M. Maghasoodi, “Analysis and Simulation of Speed Control in DC Motor Drive By Using Fuzzy Control Based on Model Reference Adaptive Control,” Cumhuriyet University Faculty of Science Journal, 37(3), pp.197-211, (2016).

[6] Y. song, Z. Wang, D. Ding, G. Wei, “Robust Model Predictive Control under Redundant Channel Transmission with Applications in Networked DC Motor System,” International Journal of Robust and Nonlinear Control, 26(18), pp.3937-3957, (2016).

[7] B. Shahsavari, M. Maasoumy, A. Sanlovani-Vincentelli, A. Horowitz, “Stochastic Model Predictive Control Design for Load Management System of Aircraft Electrical Power Distribution,” in American Control Conference (ACC), Chicago. IL. USA, July, 2015.

[8] J.A. Rossiter, Model-Based Predictive Control: A Practical Approach, CRC Press LLC, Florida, 2004.

[9] W. Wei, J. Ruo-Jun, J.Jing-Ping, “Optimal state feedback control of brushless direct-current motor drive systems based on Lyapunov stability criterion,” Journal of Zhejiang University of Science, 8(12), PP.1889-1893, (2007).

[10] S. Hui, S.H. Zak, “Observer design for systems with unknown inputs,” International Journal on applied Mathematics and Computer Science, 15 (4), pp. 431-446, (2005).

[11] T. Soubdhan, J.Ndong, H.Ould-Baba, M.Do, “A robust forecasting framework Based on Kalman Filtering Approach with a two-fold parameter tuning procedure: Application to solar and photovoltaic prediction,” Journal of Solar Energy, 131, pp. 246-259, (2016).

[12] S.E.Azam, E.Chiazi, C. Papadimitriou, “A dual Kalman filter approach for state estimation via output-only acceleration measurements,” Journal of Mechanical Systems and Signals Processing, 60-61, pp. 866-886, (2015).

[13] S.C. Maheriya, P.A. Parikh, “A Review: Modeling of Brushed DC Motor and Various types of Control Methods,” Journal for Research, 01(12), pp. 18-23, (2016).

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