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Speed Control for a Two-Mass Drive System Using Integrated Fuzzy Estimator and Hybrid Fuzzy PD/PI Controller

Neng-Sheng Pai1∗, and Yi-Pin Kuo2
1Department Of Electrical Engineering, National Chin-Yi University of Technology, 41101, Taiwan, R.O.C.
2Department of Electronic Engineering, Far East University, Taiwan, R.O.C.

Email: pai@chinyi.ncut.edu.tw

Abstract. This paper presents a novel speed control scheme for a 2-mass motor drive system. The speed controller is based on the estimated state feedback compensation. The integrated fuzzy observer can give a fast and accuracy estimation of the unmeasured states. Two kinds of hybrid fuzzy proportional-derivative and proportional-integral (HF PD/PI) are proposed to cope with this speed control problem. The first is the static HF PD/PI controller and the second is the dynamic one. Simulation results show that the developed integrated fuzzy observer provide the better estimation performance than that of the Kalman filter and the proposed control schemes can effectively track the desired speed in the presence of load disturbance.

1. Introduction

It is known that the undesirably mechanical vibration of the rolling mill drive system imposes severe limitations on the dynamic performance [1-3]. The basic limitation is that only the slow and small change of the reference command is allowed. In addition, suppose the reference command is abrupt change, the motor speed and load speed can be very different in the transient state. To solve these problems, many methods [1-3] based on various control algorithms have been examined in the last decade. The state feedback control algorithm is one of the most promising focuses on the vibration suppression [4-6]. Suppose the load torque is considered as a serious load disturbance, Kalman filter [4] is a good choice to estimate the state of load torque. However, some parameters of the drive system are not constant, a proper controller should be designed to accomplish the speed control. The fuzzy logic has been one of the best decision-making mechanisms for uncertainty signal and system [7, 8]. In this paper, we propose a novel framework of state observer, a fuzzy logic based Kalman filter is presented to speed up the estimation. It has been seen that conventional PI controllers generally do not work well for complex systems, such as nonlinear systems, higher order linear systems and systems with time delay. Recently, various fuzzy logic controllers such as fuzzy PI type, fuzzy PD type and fuzzy PID type have been applied in many fields [9,10]. In this paper, a hybrid fuzzy PD/PI controller is first proposed to provide asymptotic tracking of a reference speed for 2-mass drive system, where the large overshoot in the transient response can not be removed. Then a dynamic HF PD/PI controller based on a heuristic fuzzy logic approach is developed to improve the transient response and compensate the load disturbance of the 2-mass drive system.

2. Modeling of the two mass drive system

* To whom any correspondence should be addressed.
The mechanical structure of the rolling mill drive system can be treated as a 2-mass model. The viscosity coefficients are very small in this system so they can be neglected without affecting analysis accuracy. The dynamic equation of the model can be described as

\[ \dot{X}_m(t) = A_m X_m(t) + B_m u(t) + w(t) \]
\[ Y(t) = C_m X_m(t) + v(t) \]

where

\[ A_m = \begin{bmatrix} 0 & 0 & -1 / J_M & 0 \\ 0 & 0 & 1 / J_I & -1 / J_s \\ K_{SH} & -K_{SH} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad B_m = \begin{bmatrix} 1 / J_M \\ 0 \\ 0 \\ 0 \end{bmatrix}, \]

\[ C_m = [1 \ 0 \ 0 \ 0]^T, \quad X_m = [\omega_M \ \omega_L \ \theta_M \ \theta_L]^T, \quad Y = \omega_M, \quad u = T_M \]

\( w(t) \) is the process disturbance, and \( v(t) \) is the measurement noise. Both \( w(t) \) and \( v(t) \) are assumed to be zero-mean white Gaussian noise with the covariance matrices \( Q \) and \( R \), respectively. The meaning of the variables and parameters are given below. \( \omega_M \): the motor speed, (rpm), \( \omega_L \): the load speed, (rpm), \( T_M \): the motor torque, (N-m), \( T_{SW} \): the shaft torque, (N-m), \( J_I \): the load inertia, (kg-m\(^2\)), \( J_s \): the load inertia, (kg-m\(^2\)), \( K_{SH} \): the spring coefficient (stiffness, N-m/rad). Following the standard sample data method [11], one can easily obtain the discrete model of the system

\[ X_m(k+1) = A_{wd} X_m(k) + B_{wd} U(k) + \Gamma W(k) \]
\[ Y(k) = C_m X_m(k) + V(k) \]

where \( A_{wd} = \exp(A_M T_s) \), \( B_{wd} = \int_0^{T_s} \exp(A_M (T_s - \tau)) B_{wd} d\tau \), \( \Gamma = \int_0^{T_s} \exp(A_M (T_s - \tau)) d\tau \), and \( T_s \) is the sampling period.

To implement the state feedback control, we should get all the state variables. But it is difficult to measure internal states such as the load speed and the shaft torque in practical application for a mill drive system. Moreover, the disturbance load, an unknown input to the system should be detected as soon as possible. The algorithm of a novel observer will address in detail in the next section. At first, the commonly used Kalman filter [12] for the system (3) can be organized as follows.

Predicting stage:

\[ \hat{X}_m(k+1) = A_{wd} \hat{X}_m(k) + B_{wd} U(k) \]
\[ P(k+1,k) = A_{wd} P(k,k) A_{wd}^T + Q_d \]

where

\[ Q_d = \int_0^{T_s} A_{wd} Q A_{wd}^T d\tau \]

Updating stage:

\[ K(k+1) = P(k+1,k) C_m^T (C_m P(k+1,k) C_m^T + R)^{-1} \]
\[ P(k+1,k+1) = P(k+1,k) - K(k+1) C_m P(k+1,k) \]
\[ \hat{X}_m(k+1,k+1) = \hat{X}_m(k+1,k) + K(k+1) \{ Y(k+1) - C \hat{X}_m(k+1,k) \} \]

where \( \hat{X}_m(k+1,k) \) and \( \hat{X}_m(k+1,k+1) \) denote the predicted and updated state vectors, respectively, \( K(k+1) \) is the Kalman filter gain matrix, \( P \) is the error covariance matrix, and \( \{ Y(k+1) - C \hat{X}_m(k+1,k) \} \) is the so-called innovations vector.

### 3. Integrated Fuzzy Observer

The objective in this section is to develop an integrated fuzzy observer, which is based upon the traditional Kalman filter and the fuzzy decision logic, such that the estimated states can approach to the true states as soon as possible. The innovations vector will be introduced as a fuzzy variable. The basic idea is to compensate Kalman filter by adding fuzzy correction gains, which are determined by
the innovations vector and its rate of change. The innovations vector and the rate of change in innovations vector are defined respectively as

$$\text{error}_Y(k) = Y(k) - \hat{Y}(k)$$

$$\text{error}_{DY}(k) = \text{error}_Y(k) - \text{error}_Y(k-1)$$

where $\hat{Y}(k) = C_u \cdot \hat{X}(k)$. Then we let the fuzzy correction gain $FCG$ be

$$FCG = \text{fuzzy}(\text{error}_Y(k), \text{error}_{DY}(k))$$

where $FCG = \text{fuzzy}(Y_{error}(k), Y_{error}(k))$ indicates the fuzzy linguistic decision function which is represented as the following form,

$$\text{fuzzy}(k) = \tilde{A} \text{ and } \text{fuzzy}(k) = \tilde{B}, \text{ then } FCG = \tilde{C}$$

where $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ are the fuzzy term-sets of $Y_{error}$, $DY_{error}$ and $FCG$, respectively. The inference (14) is the so-called Mandani type implication. The defuzzification strategy is implemented by the weighted average method,

$$fcg(k) = \left( \sum_{j} c_j \cdot \mu_{jFCG} \right) / \left( \sum_{j} \mu_{jFCG} \right)$$

where $\mu_{jFCG}$ is the maximum membership function value of each term set of the fuzzy gain $fcg(k)$ and $c_j$ is the fuzzy singleton of each term set. The purpose of the Kalman filter is to decrease the difference of $Y(k) - C_u \cdot \hat{X}(k+1,k)$ such that the observed states can approach to the true states as soon as possible. From the updating stage of the Kalman filter, one can easily understand that if an extra amount is added to the difference of $Y(k) - C_u \cdot \hat{X}(k+1,k)$, then the $\hat{X}(k+1,k+1)$ will get bigger correction. The designed state observer with the introduced $FCG$ will give a larger correction than just with the conventional Kalman filter. From the simulation results shown in Section 5, one will find that its transient response is really meliorated. At the steady state, the estimation error will be within the tolerable error region, and then $FCG$ is zero and the Kalman filter takes in charge of the estimation mission. The integrated fuzzy state observer is listed as the following equations,

$$\hat{X}_u^f(k+1,k) = A_{ud} \hat{X}_u^f(k,k) + B_{ud} U(k)$$

$$\hat{X}_a(k+1,k+1) = \hat{X}_a(k+1,k) + K(k+1) \cdot \{ Y(k+1) - C \hat{X}_u^f(k+1,k) \} + f_{cg}(k)$$

where $K(k+1)$, $P(k+1,k)$, and $P(k+1,k+1)$ are determined by,

$$P(k+1,k) = A_{ud} P(k,k) A_{ud}^T + Q_u$$

$$K(k+1) = P(k+1,k) C_a^T \{ C_u P(k+1,k) C_u^T + R_u \}^{-1}$$

$$P(k+1,k+1) = P(k+1,k) - K(k+1) C_u P(k+1,k)$$

From above equations, we can find that the integrated fuzzy state observer is on the basis of the Kalman filter. In fact, (18)-(20) are the same as those in the Kalman filter.

4. Hybrid Fuzzy PD/PI Controller

All the internal state variables (shaft torque and load speed) and load disturbance (load torque) can be accurately and fast estimated by above integrated fuzzy observer. However, a delay time between the estimated states and the true states still exists when the reference speed and/or the load torque change. It is difficult for the conventional fuzzy PI controller to work well in transient responses due to the internal integrating control action. Consequently, the fuzzy PD control should be introduced. For a speed control servo system, it is required that the output speed follows the reference command without steady-state deviation, therefore an integrator is needed in the control system. In order to cope with this complicated problem, we propose the structure of HF PD/PI controller in the driver system. The block diagram of the proposed control system is configured as figure 1. The schematic diagram of the 2-mass drive system is shown in figure 2. To describe two kinds of HF PD/PI controllers, we adopt a switch to select the static HF PD/PI or the dynamic HF PD/PI controller.
4.1. Static HF PD/PI controller

Consider the static HF PD/PI controller, we combine a fuzzy PI controller with a fuzzy PD controller in parallel. Their rules can be expressed as follows.

\[
\begin{align*}
R_{PD}^p: \text{If } e(k) \text{ is } E^p \text{ and } \Delta e(k) \text{ is } \Delta E^p, \text{ then } c_{pg}(k) \text{ is } C^p \\
R_{PI}^p: \text{If } e(k) \text{ is } E^p \text{ and } \Delta e(k) \text{ is } \Delta E^p, \text{ then } \Delta c_{pg}(k) \text{ is } \Delta C^p
\end{align*}
\]  

The inputs of the controller are \( e(k) = \omega_{ref} - \dot{\omega}(k) \), which is the error between reference and estimated load speed, and \( \Delta \omega(k) \) is the change rate of the error, the fuzzy control values are \( \Delta c_{pg}(k) \) and \( c_{pg}(k) \), and \( \{ E^p, \Delta E^p, C^p \} \) and \( \{ \Delta E^p, \Delta \Delta E^p, \Delta C^p \} \) are the fuzzy sets of the inputs and output for fuzzy PD and fuzzy PI controllers, respectively.

The final outputs of the fuzzy PD and PI controller are respectively presented by

\[
\begin{align*}
u_{PD} & = u_{PD}(k - 1) + c_{pg}(k) \\
u_{PI} & = u_{PI}(k - 1) + K_P \Delta c_{pg}(k)
\end{align*}
\]  

where \( K_{PD} \) and \( K_{PI} \) are the denormalized factor of the fuzzy logic controller. The control algorithm for static HF PD/PI controller is

\[
u(k) = u_{PD}(k) + u_{PI}(k) = u_{PD}(k - 1) + K_{PD} \Delta c_{pg}(k) + K_{PI} c_{pg}(k)
\]  

The fuzzy control rules of \( \Delta c_{pg}(k) \) and \( c_{pg}(k) \) are designed by the so-called fuzzy sliding mode control.
4.2. Dynamic HF PD/PI controller

Dynamic HF PD/PI controller is developed to improve transient performance by decreasing the integral action and to maintain the zero steady-state error by increasing the integral action. Based on above requirement, the dynamic HF PD/PI controller in this paper can be obtained by combining the fuzzy PD controller and the fuzzy PI controller with a weighting factor, which is described as

$$\hat{u}(k) = \rho(k) u_{PD}(k) + u_{PI}(k)$$  \hspace{1cm} (25)$$

where $0 \leq \rho(k) \leq 1$ is the weighting factor for integral action. Substituting equations (22) and (23) in the equation (25), we obtain

$$\hat{u}(k) = \rho(k) \left( u_{PD}(k-1) + K_{PD}\Delta \hat{c}_{m}(k) \right) + K_{PI}c_{PI}(k)$$  \hspace{1cm} (26)$$

Equation (26) will be referred to as the dynamic HF PD/PI law throughout the paper. Note that if $\rho(k) = 1$, (26) is identical to the static HF PD/PI controller (24), and if $\rho(k) = 0$, equation (26) is equal to the conventional fuzzy PD controllers without integral accumulated action. Furthermore, to prevent jerkiness from abruptly changing the weighting factor, we determine $\rho(k)$ by means of fuzzy logic. In fact, both load torque and reference speed variation will result in the torsional vibration problem. It is clear that the load torque drops abruptly, once a step increment of the desired speed occurs. In addition, an impact speed drops in the cause of the external load torque. Thus, the weighting factor $\rho(k)$ is determined dependent on the estimated torque $(\hat{T}_L)$ and the error between reference and estimated load speed, and is described by the fuzzy rules,

$$\text{If } e(k) \text{ is } \hat{E} \text{ and } \hat{T}_L(k) \text{ is } \hat{T} \text{ then } \rho(k) \text{ is } \hat{\Lambda}$$  \hspace{1cm} (27)$$

where $\hat{E}$, $\hat{T}$ and $\hat{\Lambda}$ are the fuzzy term-sets of $e(k)$, $\hat{T}_L(k)$ and $\rho(k)$, respectively. The universes of discourses of $e(k)$, $\hat{T}_L(k)$ and $\rho(k)$ are partitioned into five fuzzy sets. In transient response we should decrease the integral action to speed up the motor, that is $\rho(k)$ can be assigned at zero fuzzy subset. In steady state we should increase the integral action in order to decrease the steady-state error, that is $\rho(k)$ can be selected at the very big fuzzy subset. In addition, $\rho(k)$ should be enlarged as the load is increased.

5. Simulation results

Consider the two-mass motor drive control system shown in figure 3, the initial conditions are $\omega_M(0) = 800 \text{ rpm}$, $\omega_L(0) = 800 \text{ rpm}$, $T_{Ml}(0) = 0 \text{ N-m}$, and $T_{Ll}(0) = 0 \text{ N-m}$. The sampling time is 5ms; the standard deviations of random disturbance and measurement noise are 20 and 2, respectively. The motor inertia $J_M$ is 0.1766 kg m$^2$, the load inertia is 0.1746 kg m$^2$, and the spring coefficient is 695.567 N m rad$^{-1}$ [4]. The initial settings for the Kalman filter and the integrated fuzzy observer are selected as that the initial estimated state $\hat{x}$ is a zero vector and the error covariance $P = 0.1 I_4$ ($I_4$ is 4x4 identity matrix). Firstly, for the comparison of three different estimated methods, which are typed as (a) all of the feedback states are directly measurable, (b) the feedback states are estimated by the traditional Kalman filter, and (c) the feedback states are estimated by the integrated fuzzy observer (where $K_{PD} = 60$ and $K_{PI} = 2$), we increase the desired speed $\omega_M$ from 800 rpm to 1000 rpm. figure 4 illustrates the behavior of estimation, where the integrated fuzzy observer provides faster tracking ability in all state estimation than that of the Kalman filter. Secondly, figure 5 demonstrates that the proposed dynamic HF PD/PI controller indeed improves the transient performance in comparison with the static HF PD/PI controller. The overshoot is reduced from 3.2% to 1.9%. Finally, it is seen from figure 6 that the estimated motor speed and load speed are still close to the real state even the load torque is changed from no load to 150 N-m applied at 1.1 second.
Figure 3. Block diagram of 2-mass model

Figure 4. The results of state estimate

Figure 5. The step responses of the static HF PD/PI controller and the dynamic HF PD/PI controller.
6. Conclusions

A simple novel observer based on the fuzzy decision logic and Kalman filter has been proposed in this paper. The integrated fuzzy observer possesses the better estimation ability to offer accurate as well as fast observed states for state feedback control. The dynamic HF PD/PI controller has been used to obtain proper compensation for system response by adjusting the weighting factor. The proposed control approach is evaluated in a 2-mass drive system. The results of simulation show that the integrated fuzzy observer is indeed effective and the proposed controller design is satisfactory.

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References


