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Dynamic Optimization of Feedforward Automatic Gauge Control Based on Extended Kalman Filter

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Abstract: Automatic gauge control is an essentially nonlinear process varying with time delay, and stochastically varying input and process noise always influence the target gauge control accuracy. To improve the control capability of feedforward automatic gauge control, Kalman filter was employed to filter the noise signal transferred from one stand to another. The linearized matrix that the Kalman filter algorithm needed was concluded; thus, the feedforward automatic gauge control architecture was dynamically optimized. The theoretical analyses and simulation show that the proposed algorithm is reasonable and effective.

Key words: automatic gauge control; feedforward control; extended Kalman filter

In conventional gauge control system for hot strip finishing mill, the thickness sensor is generally located in the delivery side of the last stand, and therefore, the feedback information adopted by the gauge meter automatic gauge control (GM-AGC) is not the measured data; otherwise, it is calculated through gauge meter equation[1]. Thus, the time delay occurs inevitably. To overcome and compensate the shortage of GM-AGC, the feedforward automatic gauge control (FF-AGC), as a forecasting control method, has been widely introduced into the gauge control system. FF-AGC belongs to an open loop system, and therefore, the measured gauge value as compared with the reference value does not match the dynamic condition of the rolling system[2]. In addition, stochastic factors always influence the accuracy of the gauge control system. To improve the quality of automatic gauge control (AGC), the Kalman filter is employed into the FF-AGC system.

Kalman filter is a predicted strategy based on linear regression. It can be divided into three stages: the measurement of modification, the statement of modification, and the statement of forecasting. Extended Kalman filter (EKF) can deal with nonlinear process based on the linearization of the process. In this study, the forecasting mechanism of EKF was utilized to improve the accuracy of FF-AGC, and the theoretical analyses and simulation show that the proposed algorithm is reasonable and effective.

1 Model of FF-AGC

Generally, FF-AGC is used in combination with GM-AGC and MON-AGC (monitor AGC). Firstly, the exit gauge value h_{n-1} ($n = 1, \cdots, 6$) of the previous stand is used as the entrance gauge value H_n ($n = 2, \cdots, 7$) of the next stand, and by comparing H_n and the given reference value of gauge H_r, the gauge bias ΔH can be obtained using the formula $\Delta H = H_r - H_n$. Secondly, the hydraulic capsules are regulated in advance according to ΔH and the time that the strip goes into the next stand. The mathematical model of FF-AGC can be expressed as follows:

$$\Delta S = \frac{M}{C_P} \Delta H \tag{1}$$

where ΔS is the regulated value of mill gap; M is the strip modulus, which is a function of rolling temperature T and the chemical component of the rolled material c, that is, $M = f(T, c, H_n)$ $Q = f(T, C, H_n)$; and C_P is the mill modulus of a stand.

When the strip is milled, there are various sources of process uncertainty such as un-modeled process disturbances, unknown variability in the

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rolling process, and deterioration or malfunction of the rolling equipment. All stochastic modeling of the uncertainty will transfer from the previous stand to the next stand, and thus, the control quality will gradually worsen. If appropriate measures are not taken, the control accuracy of FF-AGC will be limited. A typical structure of FF-AGC is shown in Fig. 1.

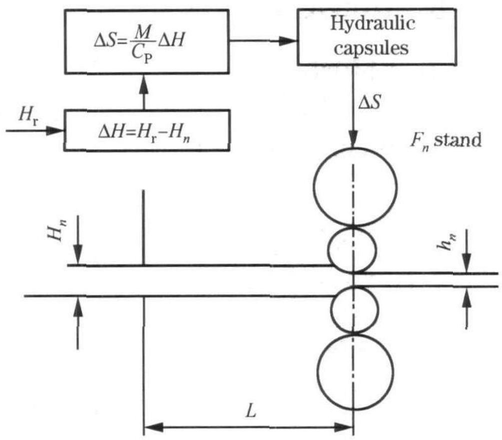

Fig. 1 Structure of FF-AGC control

2 Algorithm of EKF

Prior to using the Kalman filter, the control system should be described as the state-space equation and the observed equation. For a nonlinear system, it should first be linearized before using the Kalman filter; this is the so-called EKF. Then, the estimated value at a certain time k can be calculated according to the observed data of previous time and the predicted value of last time. This estimated value is revised via transcendental estimated state value and the error covariance. Then, the transcendental estimated state value and the error covariance at time $k+1$ can be forecasted.

To compensate the transferred time delay, the delayed measured data promulgates with the estimated value of the filter. The optimized estimated value filtered noise is gained based on the error estimated rule of linear un-bias minimum average[3]. A typical Kalman filter algorithm can be expressed as follows[4-6]:

Firstly, define the state equation and the observed equation of the system as follows:

$$x(k+1) = Ax(k) + Bu(k) + \Gamma w(k) \tag{2}$$

$$y(k) = Cx(k) + v(k) \tag{3}$$

where $x(k)$ is the state vector of dimensions n; $u(k)$ is the control vector of dimension m; $w(k)$ is the white noise process of dimension p; $y(k)$ is the observed vector of dimensions r; $v(k)$ is the observed noise of dimension r; A, B, C, and Γ are the coefficient matrix, the control matrix, the observed matrix, and the process noise matrix of appropriate dimensions, respectively. $w(k)$, $v(k)$ denote a noise source with normal distribution, $w(k) \sim N(0, Q_n)$, $v(k) \sim N(0, Q_n)$.

Secondly, take the observed data $\{y(1), y(2), \cdots, y(k)\}$ before time k, and define "$\wedge$" as the filter value of the relative variable. Then, the state estimate before test is defined as:

$$x(k|k) = \hat{x}(k|k-1) + Bu(k) + L(k)[y(k) - C\hat{x}(k|k-1)] \tag{4}$$

where $x(k|k)$ is $x(k)$ at time k.

The relative error covariance estimate is:

$$P(k|k) = [I - L(k)C]P(k|k-1) \tag{5}$$

where I is separator symbol.

The relative gain matrix extrapolation is:

$$L(k) = P(k|k-1)C^{T}[CP(k|k-1)C^{T} + R]^{-1} \tag{6}$$

Finally, from Eqn. (4) to Eqn. (6), the state estimate update can be obtained as Eqn. (7), and the error covariance update can be obtained as Eqn. (8).

$$x(k+1|k) = \hat{x}(k|k) + Bu(k+1) \tag{7}$$

$$P(k+1|k) = AP(k|k)A^{T} + \Gamma Q\Gamma^{T} \tag{8}$$

where Q is noise covariance matrix.

The initial conditions on the state vector and covariance are:

$$E[x(0)] = \hat{x}_0,\quad E[(x(0) - \hat{x}_0)[x(0) - \hat{x}_0)^{T}] = P_0 \tag{9}$$

where E is expectation; and P_0 is initial value of covariance.

3 Dynamic Optimization of FF-AGC Based on EKF

Since the AGC system is an essential nonlinear process, the mathematical model should be first linearized. Therefore, consider the interaction of variable when milling[3], take $x_n = [H_n\ J_n\ \sigma_n\ S_n]^{T}$, where, J_n is hardness change at stand n; σ_n is tension at the stand n; S_n is mill gap at stand n.

For stand $n+1$,

$$H_{n+1} = G_{n+1} + f_H(F_{n+1} + S_n) \tag{10}$$

where f_H is function of gauge; and G_{n+1} is compensatory value of gauge control.

By linearizing Eqn. (10), Eqn. (11) is obtained as follows:

$$\Delta H_{n+1} = \Delta G_{n+1} + \frac{\partial f_H}{\partial P_{n+1}}\Delta F_{n+1} + \Delta S_n \tag{11}$$

Setting $\frac{\partial f_H}{\partial F_{n+1}} = \frac{1}{C_{F_{n+1}}}$

The relative linearization model is:

$$\Delta H_{n+1} = \Delta G_{n+1} + \frac{\Delta F_{n+1}}{C_{F_{n+1}}} + \Delta S_n \tag{12}$$

Using the relative mathematical transformation and by rearranging, Eqn. (13) can be obtained as follows:

$$\Delta H_{n+1} = a_{11}\Delta H_n + a_{12}\Delta J_n + a_{13}\Delta\sigma_n + a_{14}\Delta S_n + w_{11}(\eta_H)_{n+1} + w_{12}(\eta_\sigma)_{n+1} \tag{13}$$

where $a_{11} = q_1 q_2 \frac{\partial f_F}{\partial H_n}$, $a_{12} = q_1 q_2 \frac{\partial f_F}{\partial J_n}$, $a_{13} = q_1 q_2 \frac{\partial f_F}{\partial \sigma_n}$, $a_{14} = q_1$, $w_{11} = q_1$, $w_{12} = q_1 q_2 \frac{\partial f_F}{\partial \sigma_{n+1}}$. $q_1 = \left(1 - \frac{1}{C_{P_{n+1}}}\frac{\partial f_P}{\partial H_{n+1}}\right)^{-1}$; $q_2 = \frac{1}{C_{P_{n+1}}}$; f_F is function of rolling force; η_H, η_σ, η_J, η_r, η_s are the added value of H, σ, J, r, and s, respectively; ΔJ is the changed value of hardness; and $\Delta\sigma$ is the change value of tension.

For variables $[J_n\ \sigma_n\ S_n]^{\mathrm{T}}$, the relative linearization model is:

$$\begin{aligned} \Delta J_{n+1} &= \Delta J_n + (\eta_J)_{n+1} \\ \Delta\sigma_{n+1} &= \Delta\sigma_n + (\eta_\sigma)_{n+1} \\ \Delta S_{n+1} &= \Delta S_n + (\eta_s)_{n+1} \end{aligned} \tag{14}$$

Its self-adapted matrix is:

$$\begin{bmatrix} \Delta J \\ \Delta\sigma \\ \Delta S \end{bmatrix}_{n+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta J \\ \Delta\sigma \\ \Delta S \end{bmatrix}_{n} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \eta_J \\ \eta_\sigma \\ \eta_s \end{bmatrix}_{n+1} \tag{15}$$

Therefore, according to Eqn. (13) and Eqn. (15), the state equation is as follows:

$$\begin{bmatrix} \Delta H \\ \Delta J \\ \Delta\sigma \\ \Delta S \end{bmatrix}_{n+1} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta H \\ \Delta J \\ \Delta\sigma \\ \Delta S \end{bmatrix}_{n} + \begin{bmatrix} w_{11} & w_{12} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \eta_H \\ \eta_J \\ \eta_\sigma \\ \eta_s \end{bmatrix}_{n+1} \tag{16}$$

Using this equation with the EKF algorithm, the filter process can be divided into three stages: firstly, the state vector x_n and the covariance vector P_n in stand n are updated, and then these vectors are extrapolated from stand n to stand $n+1$, and finally, these vectors update their values in stand $n+1$.

4 Simulations

Take one hot mill plant for example. The gauge control performance with the use of FF-AGC is shown as follows. Firstly, noise signal is added to the finishing mill system, considering the step response of stand F4 and F6 with or without EKF. Fig. 2 is the noise signal, which is added to the stand.

Fig. 3 (a) depicts the step response of FF-AGC in stand F4 without EKF when the noise signal is added. Fig. 3 (b) depicts the step response of the system with EKF. From these two charts, the system control accuracy is significantly improved. The same result can be obtained from Fig. 4, which depicts the simulation result of FF-AGC in stand F6 with

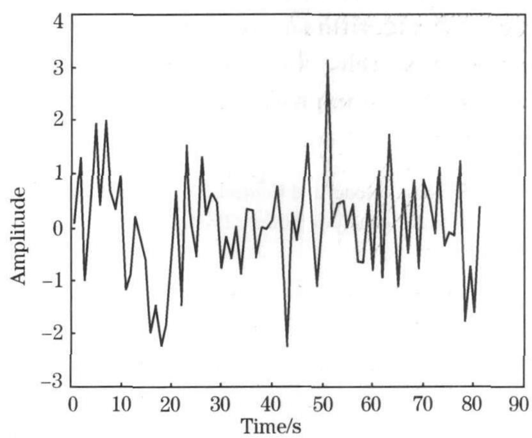

Fig. 2 Noise signal

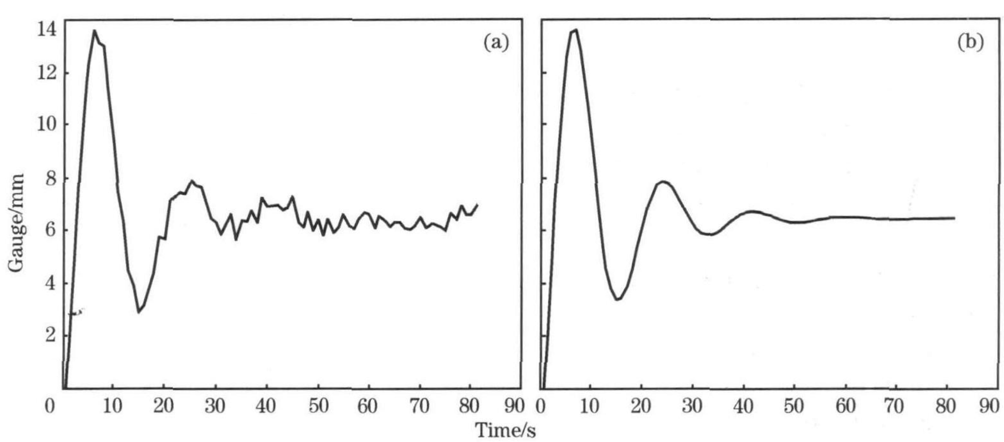

Fig. 3 Step response of FF-AGC in stand F4 without EKF (a) and with EKF (b)

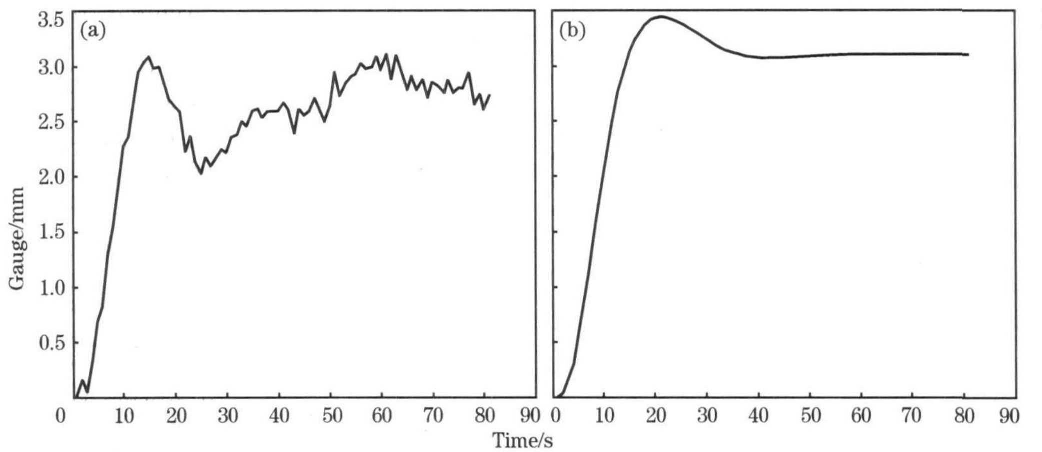

Fig. 4 Step response of FF-AGC in stand F6 without EKF (a) and with EKF (b)

or without the EKF when the noise signal is added.

5 Conclusion

EKF was introduced into FF-AGC to improve the accuracy of gauge control. Based on the simulation, it can be concluded that stochastic varying input and process noise worsen the control quality, and the EKF algorithm is reasonable and effective. For further research, the convergence data of optimization should be improved as soon as possible.

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