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The Application of Kalman Filter in Boiler Temperature Monitoring System

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Abstract: The application of Kalman filter in current digital boiler temperature control system is studied in this paper. The Kalman filter algorithm is introduced in the temperature control part and the mathematical model is established, then the corresponding filter equation is given based on the system characteristics. By using Kalman filter algorithm, the real-time tracking problem of the steam boiler temperature monitoring is solved, finally that the sampling signal filtering effect is better can be verified through mat lab simulation.

Keywords Kalman filter; Boiler temperature; Monitoring system

INTRODUCTION

The core of the industrial steam boiler is combustion system of boiler drum, which is an important index of its stable operation implementation. If the steam temperature inside the boiler is too high, it can lead to the poor separation of steam and water because of too much water in steam, and as a result of the subsequent superheater pipe wall with a lot of incrustation, the heat transfer efficiency of superheater is lowered, thus the descend of the superheated steam temperature is caused, seriously leading to the bad effect on the production and safety [N. Sivashankar *et al.*, 2013]; On the other hand, if the boiler temperature is too low, part of the water circulation system of the water wall is broken, thus it cannot meet the technological requirements, seriously leading to an explosion. Especially for large boilers, improper temperature control is easy to cause major accidents. Therefore, in the operation of boilers, to realize the control of temperature is becoming especially important.

In this paper, the digital boiler temperature control system is realized by using microcomputer and its related hardwares. The process of data collection is to use the sensors to accomplish the measurement and transmission of the temperature data, finally the temperature is indicated with light cross and LED. Inside this, the system under control adopts AD590 temperature sensor. From the viewpoint of engineering application, the Kalman filter algorithm is introduced, the mathematical model is established, then the corresponding filter equation is given based on the system characteristics.

DISCRETE KALMAN FILTER ALGORITHM

Set the estimated state X_k at the time t_k being driven by the noise sequence W_{k-1}, the state space model of the system is:

$$\mathrm{X_k = \Phi_{k,k-1} X_k + \Gamma_{k-1} W_{k-1}} \tag{1}$$

To meet the linear relationship of X_k measurement, the measurement equation is [P.shi, 2012] :

$$\mathrm{Z_k = H_k X_k + V_k} \tag{2}$$

Among them, $\Phi_{k,k-1}$ is the step transition matrix from moment t_{k-1} to t_k ; Γ_{k-1} is the system noise driving matrix; H_k is the measurement matrix; V_k is the measurement noise sequence; W_k is the system incentive noise sequence. At the same time ,W_k and V_k meet:

$$\begin{aligned} &\mathrm{E[W_k] = 0} \quad \mathrm{Cov[W_k, W_j] = E[W_k W_j^T] = Q_k \delta_{kj}} \\ &\mathrm{E[V_k] = 0} \quad \mathrm{Cov[V_k, V_j] = E[V_k V_j^T] = R_k \delta_{kj}} \\ &\mathrm{Cov[W_k, V_j] = E[W_k V_j^T] = 0} \end{aligned} \tag{3}$$

Among them , is the variance matrix of the system noise sequence Q_k and assumed to be nonnegative matrix; R_k is the variance matrix of the measurement noise sequence and assumed to be positive matrix.

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If the estimated state vector X_k satisfies the formula (1), as the measurement of X_k, Z_k satisfies the formula (2), the system noise W_k and the measurement noise V_k satisfy the formula (3), the covariance matrix of the system noise sequence Q_k is nonnegative definite, the covariance matrix of the measurement noise sequence R_k is positive definite, the value of both sides at k time is Z_k, $\hat{X}_k$, which is the estimation of X_k, can be solved according to the follow equtions[S.K. Nguang *et al.*, 2010]:

$$\hat{X}_{k/k-1} = \Phi_{k,k-1}\hat{X}_{k-1} \tag{4}$$

$$\hat{X}_k = \hat{X}_{k/k-1} + K_k(Z_k - H_k\hat{X}_{k/k-1}) \tag{5}$$

$$K_k = P_{k/k-1}H_k^T(H_kP_{k/k-1}H_k^T + R_k)^{-1} \tag{6}$$

$$K_k = P_kH_k^TP_k^{-1} \tag{7}$$

$$P_{k/k-1} = \Phi_{k,k-1}P_{k-1}\Phi_{k,k-1}^T + \Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^T \tag{8}$$

$$P_k = (I - K_kH_k)P_{k/k-1}(I - K_kH_k)^T + K_kR_kK_K^T \tag{9}$$

$$P_k = (I - K_kH_k)P_{k/k-1} \tag{10}$$

$$P_k^{-1} = P_{k/k-1}^{-1} + H_k^TR_k^{-1}H_k \tag{11}$$

Among them, formula (4) is referred to the state one step prediction equation, formula (5) is referred to the state estimation equation, formula (6), (7) are referred to the filter gain equation, formula (8) is referred to the one step prediction mean square error equation, formula (9), (10), (11) are referred to the estimation mean square error equation.

Formula (2-4) to (2-8) is the basic equation of discrete Kalman filter. As long as initial value $\hat{X}_0$ and P_0 are given , the state estimation of $\hat{X}_k$ at k time can be obtained by recursive calculation according to the measured value Z_k at k time (k=1,2...).

THE APPLICATION OF KALMAN FILTER

Kalman filter method is to use the measured values of the last state and the current state to estimate the current state, this is because the last state estimation has error to estimate the state at this moment, and the measurement of the current state also has error, so a value which is most close to the true state is estimated according to these two errors [S.K. Nguang *et al.*, 2013]. Therefore, to design a Kalman filter for the monitoring of temperature, first of all, we need to be familiar with the signal characteristics which are going to be collected, the predicted value estimated by a variety of aspects as well as the noise condition under certain environment and time. When choosing AD590 for temperature measurement, through the analysis of the related parameters of AD590 sensor, proper mathematical model is established. AD590 is the two ports integrated temperature sensor produced by ANALOG DEVICES, because of its carving process and high impedance, it has a wide application on the remote temperature monitoring.

The Establishment of the Mathematical Model

Dynamic equation can be described by the first order differential equation:

$$\tau\frac{du}{dt} + U = k(T + v) \tag{13}$$

Among them,

τ - Time constant of the transducer (S);
T- Measured temperature (oC);
U- Output voltage of the system (V);
v- Observed noise (oC);
k- Steady state gain of the system(V/oC).

Assume, without introducing the white noise, the transfer function after the transformation is expressed as:

$$F(S) = \frac{k}{\tau s + 1}, s = -\frac{1}{t} \tag{14}$$

From the formula above, the transfer function is a function of time t, after discrete Z transform we can obtain [S. Xu *et al.*, 2014]:

$$\begin{aligned} &F(z) = \frac{k}{z-a}(a = e^{T-t}) \\ &U(n+1) - aU(n) = kT(n) \\ &U(n) = aU(n-1) + kT(n-1) \end{aligned} \tag{15}$$

Or it can be written as:

$$\tau\frac{U(n) - U(n-1)}{t} + U(n) \approx kT(n) \tag{16}$$

Among them, t- sampling period of the computer:

$$\begin{aligned} &\tau[U(n) - U(n-1)] + tU(n) = ktT(n) \\ &\tau U(n) + (1-t)U(n-1) = kT(n-1) \end{aligned} \tag{17}$$

Arrange the formula and conclude:

$$U(n) \approx aU(n-1) + kT(n-1) \tag{18}$$

If the white noise is introduced, the final result is as follows:

$$U(n) = aU(n-1) + kW(n-1) \tag{19}$$

And because Kalman filter model is suitable for the time-varying signal and time-varying observation process [Zhang H., 2011].

According to the recursive equation:

$$s(n) - A_ns(n-1) = \xi(n) \tag{20}$$

The observation equation:

$$x(n) = c\hat{s}(n) + v(n) \tag{21}$$

When near the steady state or n is large, the influence of the ξ (n) is small, from the view of engineering, that is, it is expressed by the formula $A_n \approx e^{-st}$, after using of Kalman filter model, the filter equation is finally deduced [U. Shaked *et al.*, 2011] as:

$$\hat{U}(n) - A_n\hat{U}(n-1) \approx K_n[T(n) - A_n\hat{U}(n-1)] \quad (22)$$

The Selection of System Parameters

Because of the linear element AD590, the output is a linear voltage.

The selection of the hardware and its parameters are as follows:

A/D converter: PCL-818L12 input ports (produced by Yan Hua company);

Timer: use Counter0 timer;

A/D input: 5v (in the circuit design, after sample amplification, ensure that the temperature is 100oC);

Measurement system C is 0.01;

According to the expression $A_n \approx e^{-st}$,the extreme value of sampling signal can be obtained, in the design of the system software, the sampling period of computer can be set as T=50 ms, and the time constant of the system is obtained by the experiment =13.55, assuming that the noise is white noise, then according to the formula $A_n \approx e^{-st}$,we can get A_n=0.9963. That is the variance is unit 1, the parameter of the predicted noise is σ =1; $\sigma_{\xi}^2 = 1 - A_n^2 = 0.00738$.

Due to the given Kalman gain K_n = 0.0098, the filter equation is:

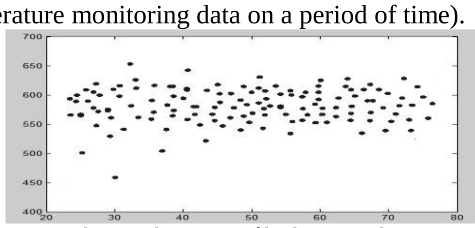
$$\hat{U}(n) = 0.9963\hat{U}(n-1) + 0.0098[T(n) - 0.9963\hat{U}(n-1)] \quad (23)$$

Because the designed Kalman filter is stable, the equation above is modified as:

$$\hat{U}(n) = 0.99\hat{U}(n-1) + 0.009T(n) \quad (24)$$

Simulation with Matlab Software

Mathematical model is established according to the formulas above, and then mat lab is used to accomplish simulation (fig. 1 is the boiler internal temperature monitoring data on a period of time).



Fiugre 1. The sampling point of boiler internal temperature

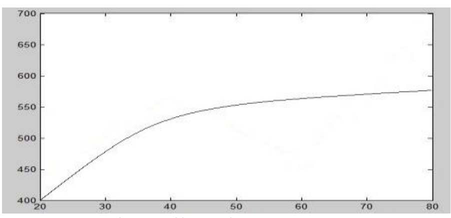


Figure 2. Kalman filter effect of boiler internal temperature sampling signal

Through the simulation result in fig. 2, Kalman filter can make the signal more smooth and have a higher degree of approximation. By using Kalman filter algorithm can solve the problem of the steam boiler temperature monitoring real-time tracking. The implementation effect seen by simulation is good.

The recognition of the water-flooded zone is largely based on the log-curves that can reflect the physical and chemical properties. After the relative analysis and statistics, according to the experience of the field experts, the writer chose spontaneous potential (SP), High resolution acoustic transit time (AC), High resolution deep lateral resistivity Rlld and the difference between micro potential and micro gradient, Rmn-Rmg, as the logging feature parameters for the recognition of the water-flooded zone's water flooded grade, and the output is the water flooded grade.

From the limited reservoir data of the core holes, we chose 450 representative water-out reservoir sample to form a training set, and 225 reservoir sample to form a test suite. According to the determination method of the pattern classes number, the water flooded grade of the reservoir can be divided into 4 situations, strong water flooding, secondary water flooding, weak water flooding and not flooded.

We deal with the 450 training samples by wavelet transform, then input the results to SVM to train. After training, we get the corresponding support vectors and weight parameters, thus getting the model as shown in Fig1.In the experiment, when we use RBF function as the kernel function; we get the most support vectors, the highest classification accuracy in a fast running speed. So we choose RBF function as the kernel function, the experiment results are shown in Table1 and Table2.

Table 1. Conditions of Supporting vectors obtained by several kernel functions

Kernel function	Parameter Setting	Quantity of supporting vector	Quantity of supporting vector in each classification			
			Strong water Flooding	Secondary water flooding	Weak water flooding	Not flooded
Rbf	d=3.0, c=1000.0 g=0.25	343	46	110	41	146
Poly	d=3.0, c=1000.0,g=0.25	250	43	83	37	87
Sigmoid	d=3.0, c=1000.0,g=0.25	269	38	86	39	106

Table 2. Conditions of training speed and accuracy obtained by several kernel functions

Kernal function	Parameter setting	Time(s)	Training Sampling Accuracy (%)	Test Sample Accuracy (%)
rbf	d=3.0,c=1000.0 g=0.25	40	90.5	78.1
poly	d=3.0,c=1000.0 g=0.25	1145	80.5	68.4
sigmoid	d=3.0,c=1000.0 g=0.25	254	78.3	65.2

When we back to judge the training sample with the studied SVM actuator, the correct recognition rate is 90.5%; when judging the 305 samples in the test suite, the correct recognition rate is 78.1%. It is a fairly good result in terms of flooded layer's automatic recognition. When the same data are used in the neural network, the sample accuracy will come to 96.4%; but the accuracy of the test suite is only 73.4%.The experiment results are shown in Table3.

Table 3. Comparison between B-SVM Algorithm and Process neural network

Algorithm	Training time(s)	Training Sample Accuracy (%)	Test Sample Accuracy (%)
B-SVM	40	90.5	78.1
Process neural network	8145	96.4	73.4

CONCLUSION

Kalman filter algorithm is applied to current digital boiler temperature control system, through the establishment of the mathematical model, and then the corresponding filter equation is given according to the system characteristics, finally Kalman filter can make the signal more smooth and have a higher degree of approximation shown from the simulation, thus that Kalman filter algorithm has a better filter effect on sampling signal is verified.

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