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The research on the fault detection based on the water level sensor network

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ABSTRACT

This model makes use of the interface between the fault detection and fault isolation, which is theoretically employed by fault characteristic matrix. The matrix records the information of correlation between the detection signal and the fault as well as corresponding time. The state characteristics of the system can be reasoned from the relation between the fault signal and the fault. We can make full used of fault signals. The occurring time of the fault can be got by conducting the discrete time method on the observed fault signal. The application of the proposed detection method to the network of mine water level sensor proved that this method is more reasonable than the standard binary fault detection method.

KEYWORDS

Sensor; Fault detection; Interval observer; Robustness.

INTRODUCTION

For the guarantee of long-term reliability and security of mines, we can never afford to ignore the check of sensorfailures. Theprinciple of mine monitoringsensoristoutilizesensorfeedbackto constructthe current mineenvironment. Should a detected signal from a fault sensor react in thefeedback link of the control law, the consequences willbedisastrous. Currently, common used methods of fault diagnosing and detecting of sensors are as follows: hardware redundancymethod, theKalmanfiltermethod, analytical redundancymethod, neural networkobservinggroupmethod[1]. Targeting at the fault detection of mine monitoring sensor, this paper adopts the intervalobserverastheestimator, thus combining the merits while overcoming the defects ofhardwareredundancymethodandanalytical redundancymethod. Monitoringsensorisusedtomeasure the various data formineproduction process and it can inputvoltage signals, which areproportionaltotheamountofparametercontent, into the controller. In this way, the monitoring sensor can deliver timely security status of the current environment. The predict accuracy by the monitoring sensor is of vital significance to workers' safety. The sensorisinstalled in the harsh underground environmentofhigh-temperature, high-pressure, high humidityand it faces manyuncertainties. Moreover, during the monitoring process,such factors asmoisture, dust, and potential irresistibleforce may cause such faults as corrosion, filament fracture and loose contact of the sensorpotentiometer, anddeformation. All these can lead to relative serious errorin measurement accuracy. Therefore,itis very necessaryto carry out real time examination of the minesensor. This paper takes the minewater level sensor as an example foranalysis.

PRINCIPLES OF SYSTEM

The role of mine water level monitoring is to preventsudden rise in mine water level resulting from such factors as floodsand improvetheperformance ofreal-time monitoring. However, duetothecomplexityoftheunderground environment, these sensorsare likely to undergo faults because of corrosion. If suchfaultscan not beendetectedand isolated, theconsequenceswould be disastrous. An effectivedetectionmethod isonline fault detection and isolation(FDI). There are two waysofsolving theFDIproblem: the hardwareredundancymethod(forcomplex environmentssuchas the outer space), software redundancylaw(applicable to large-scale monitoringsystem). Taking into account thecostandapplicationenvironment, this paperselects the latter option. The applicationofthestandardFDI encounters many shortcomings. This is mainly because of the adoption of the simple binarymethod for the interface between fault detectionandfault isolation nature of fault signals. In order to improvetherobustnessofthe modelerror, thispaper proposesthe interval observermethod, in which information of fault characteristicmatrix is added to thetraditionaldual structure. The information includes theresidualfaultsensitivity and residualtime etc. The fault signal will be indicated in the form of discrete event sequence by the intervalobserver.

Traditional FDI method

According to a series of fault indicationsignals of residuals $r(k)$, the expression of $r(k)$ of the monitoring system of thefault detection andisolation(FDI) model can be shown as follows:

$$r(k)=\Psi(y(k),u(k)) \tag{1}$$

$u(k)$ and $y(k)$ are respectively stand for measurementinputand measurement output and Ψ represents residual generatingfunction, which canmeasurethe input and outputofthesystem at any time. In the ideal situation of no error, the residual value is zero. The occurrence of a faultdepends onthe relative value of each residual $r_i(k)$ in relation to the threshold,external interference, system uncertaintiesas well asnoises. These measurements of residualsgive birth to the fault characteristic $\phi(k)=[\phi_1(k),\phi_2(k),...,\phi_n(k)]$. Themostsimple method of observingfault signalcomparingtheresidual andthethreshold value:

$$\phi_i(k)=\begin{cases}0, if\ |r_i(k)|\le\tau_i\\ 1, if\ |r_i(k)|>\tau_i\end{cases} \tag{2}$$

The observed fault characteristics will be sent to the fault isolation module for isolation.

The binary relation between fault sequence $f(k)=[f_1(k),\ f_2(k),...,\ f_n(k)]$ andfaultsignalsequence $\phi(k)$ iscalledthebinaryfaultcharacteristic matrix(FSM)theory. That is to say, when the value of an elementofthematrix FSM_{ij} is one, it means that there is fault. However, suchbasicFDImechanismhas the following disadvantages: 1) τ_i must be able to conceive the uncertainties of the system according to thesysteminput and outputuncertainty and then conduct online self-adaption. 2) Noise maygeneratechattering3) according to the fault characteristic matrix, the fault can only be detected in the case that it can be observed in the entirefault isolationstage; however, fault signals are dynamic in nature, so it can not necessarilymeetthe above requirement. 4) Owing to the binary relation between faultandthe faultsignal, some usefulinformationfor improvingresolution and accuracymay be lost.

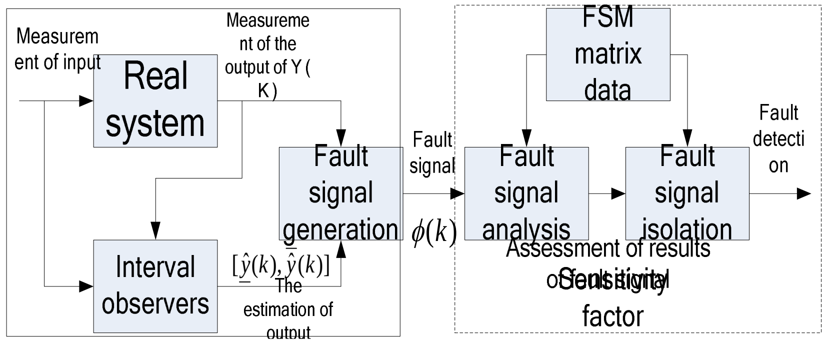

Figure 1 : Detection System of Fault h

Improved FDI method

The purposeofthefault detectionisto produce fault signalfor fault prediction. Thefault detection algorithm should have guaranteed robustness, namely, abletodeal with uncertainties. The robustness is determined by the comparison of the algorithm's sensitivity to faultand uncertainty (model error and interference). This paper adopts a passivealgorithm and self-adaptive threshold in the decision-makingstageso as to improve the robustness. Diagram 1 showsa general structure ofthis method.

The dynamic model of linearuncertaindiscretetime by FDImethod for multi-inputmulti-output monitoring system can be illustrated as the subsequent formula:

$$x(k+1) = A(\tilde{\theta})x(k) + B(\tilde{\theta})u_0(k) + F_a(\tilde{\theta}) f_a(k)$$
$$y(k) = c(\tilde{\theta})x(k) + F_y(\tilde{\theta}) f_y(k) \quad \textbf{(3)}$$

Wherein, $y(k)$, $u_0(k)$,and $x(k)$ respectively represent system input, output, and state spatialvector; $A(\tilde{\theta})$, $B(\tilde{\theta})$,and $c(\tilde{\theta})$ are correspondingstate, inputandoutput matrixes; $\tilde{\theta}$ is the systemparameter vector; $f_y(k)$ and $f_a(k)$ are faults happening to sensor and actuator; $F_y(\tilde{\theta})$ and $F_a(\tilde{\theta})$ are corresponding adjoint matrixes to $f_y(k)$ and $f_a(k)$.

The performance of the illustrated monitoring system based on interval model is realized by the linearobserver. This model assumes that parameter θ is time-varying and it belongstotheinterval $\Theta = \left\{\theta \in R \mid \underline{\theta} \le \theta \le \overline{\theta}\right\}$, which showstheuncertaintyof thereal system parameter $\tilde{\theta}$. Theobtainedintervalobservercan be expressedas follows:

$$\hat{x}(k+1) = (A(\theta) - \Lambda c(\theta)\hat{x}(k) + B(\theta)u(k) + \Lambda y(k))$$
$$\hat{y}(k) = c(\theta)\hat{x}(k) \quad \textbf{(4)}$$

u stands for the spatial state vector of systemmeasuringinputvector $\hat{x}(k)$ and $\hat{y}(k)$ is a vector for measuring the systemoutput. Themeasurement systeminput and systemreal inputthefollowing formula:

$$u(k) = u_o(k) + F_u(\theta) f_u(k) \quad \textbf{(5)}$$

$f_u(k)$ stands for inputfault of the sensor and $F_u(\theta)$ is the correspondingadjoint matrix.

The design of the observer gainmatrix Λ should ensurethe stabilityofmatrix $A_o(\theta) = A(\theta) - \Lambda C(\theta)$. The transient response of the uncertain parameter θ to the observer enablestheintervalobserver to estimate thesystem outputat any time; hence, eachoutput $\hat{y}(k)$ is withintheintervalbetween $[\underline{\hat{y}}(k), \overline{\hat{y}}(k)]$:

$$\underline{\hat{y}}_i(k) = \min_{\theta \in \Theta}(\hat{y}_i(k)) \ \overline{\hat{y}}_i(k) = \max_{\theta \in \Theta}(\hat{y}_i(k)) \quad \textbf{(6)}$$

Such interval estimationcan be obtainedthroughnumerical optimizationalgorithm [3]; ifthere is no fault, the system output satisfies the following formula:

$$y_i(k) \in [\underline{\hat{y}}(k), \overline{\hat{y}}(k)] \quad \textbf{(7)}$$

Taking into account the initialcondition, formula (4)can be rewritten intotheinput and outputforms:

$$\begin{aligned} \hat{y}(k) &= G(q^{-1},\theta)u(k) + H(q^{-1},\theta)y(k) \\ &= G(q^{-1},\theta)u_0(k) + H(q^{-1},\theta)y(k) + G_{fu}(q^{-1},\theta) f_u(k) \end{aligned} \quad \textbf{(8)}$$

Wherein

$$G(q^{-1},\theta) = C(\theta)(qI - A_o(\theta))^{-1} B(\theta) \quad \textbf{(9)}$$

$$H(q^{-1},\theta) = C(\theta)(qI - A_o(\theta))^{-1} \Lambda \quad \textbf{(10)}$$

$$G_{fu}(q^{-1},\theta) = G(q^{-1},\theta) F_u(\theta) \quad \textbf{(11)}$$

The expression of residual is as follows:

$$r(k) = y(k) - \hat{y}(k) \quad \textbf{(12)}$$

According to formula (8), the residual expression can be shown as follows:

$$r(k) = -G(q^{-1},\theta)u(k) + (I - H(q^{-1},\theta))y(k) \quad \textbf{(13)}$$

The formula of unknown input impact can be obtained with the help of formulae(8),(12), and(13):

$$\begin{aligned} r(k) &= r_\theta(k) + (I - H(q^{-1},\theta))(G_{fa}(q^{-1},\tilde{\theta}) f_a(k) \\ &\quad + G_{fy}(q^{-1},\tilde{\theta}) f_y(k)) - G_{fu}(q^{-1},\theta) f_u(k) \end{aligned} \quad \textbf{(14)}$$

Wherein:

$$r_\theta(k) = -G(q^{-1},\theta)u_0(k) + (I - H(q^{-1},\theta))y_0(k) \quad \textbf{(15)}$$

$$G_{fa}(q^{-1},\tilde{\theta}) = C(\tilde{\theta})(qI - A(\tilde{\theta}))^{-1} F_a(\tilde{\theta}) \quad \textbf{(16)}$$

$$G_{fy}(q^{-1},\theta) = F_y(\tilde{\theta}) \quad \textbf{(17)}$$

When the residual is not influenced by system faults but only by structural uncertain parameters, the formula can be written as $r_\theta(k)$. In this case, we consider the passive impact of uncertain parameters on the robustness. Estimate the residual and use the interval observer of formula (4) to get the nominal model $\hat{y}^o(k,\theta^o)$; make $\theta = \theta^o \in \Theta$; then comes the residual estimation formula:

$$r^o(k) = y(k) - \hat{y}^o(k) \quad \textbf{(18)}$$

In the ideal situation of no error, the value of $r^o(k)$ shall be zero. However, due to the unknown input disturbance and model error, this assumption was not solid. Error will spread from interval observer to residual makes nominal residual in the interval changes:

$[\underline{r}_i^o(k), \overline{r}_i^o(k)]$ **(19)**

Wherein: $\underline{r}_i^o(k) = \underline{y}_i(k) - \hat{y}_i^o(k)$ $\overline{r}_i^o(k) = \overline{y}_i(k) - \hat{y}_i^o(k)$ **(20)**

$\underline{\hat{y}}_i(k)$ and $\overline{\hat{y}}_i(k)$ are estimated minimum and maximum output value of system i according to formula (6). The interval given by formula (19) can be viewed as adaptive threshold value:

PRODUCTION OF FAULT SIGNAL

The measuring noise of the sensor can lead to unstable shaking. The gradual reasoning method can avoid the shaking[4]. Apply the Cramer equation on each residual and then the fault detection signal can be showed as follow:

$$\phi_i(k) = \begin{cases} \dfrac{(r_i^o(k)/\overline{r}_i^{\,o}((k))^4}{1+(r_i^o(k)/r_i^{\,o}((k))^4}, & if\ r_i^o(k) \geq 0 \\ -\dfrac{(r_i^o(k)/\overline{r}_i^{\,o}((k))^4}{1+(r_i^o(k)/r_i^{\,o}((k))^4}, & if\ r_i^o(k) \leq 0 \end{cases}$$ **(21)**

Formula (21) transform residual into step-by-step form,

$\phi_i(k) \in [-1,1]$. When $|\phi_i(k)| \geq 0.5$, it is assumed as a fault signal; otherwise, no fault signal.

Dynamic nature of fault signal

The dynamic characteristic of the fault signal $\phi_i(k)$ can be shown by the comparative sensibility of residual $r_i(k)$ to fault f_j. According to reference[5],the residual sensitivity can be expressed as follows:

$$S_f(q^{-1}) = \frac{\partial r}{\partial f}$$ **(22)**

Therefore, the residual sensibility is the transfer function of the impact of fault to residual. This concept is of great importance to the quality fault detection and occurring time of fault.

With formula（14） and formula（22）, we can obtain the residual sensitivity of f_y, f_u ,and f_a.

$$S_{fy}(q^{-1},\theta) = (I - H(q^{-1},\theta))G_{fy}(q^{-1},\tilde{\theta})$$ **(23)**

$$S_{fu}(q^{-1},\theta) = -G(q^{-1},\theta)F_u(\theta)$$ (24)

$$S_{fa}(q^{-1},\theta) = (I - H(q^{-1},\theta))G_{fa}(q^{-1},\tilde{\theta})$$ **(25)**

S_{fy}, S_{fu} and S_{fa} are respectively the fault sensitivity of f_y, f_u, and f_a.

Substitute formulae （23）—（25）into formula （14）, and we can obtain the formula for residual sensitivity:

$$r(k,\theta) = r_\theta(k,\theta) + S_{fa}(q^{-1},\theta) f_a(k) \\ + S_{fy}(q^{-1},\theta) f_{fy}(k) + S_{fu}(q^{-1},\theta) f_{fu}(k)$$ **(26)**

Design of fault detection and isolation

Normally, fault detection and fault isolation are two separate modules. The typical interface of these modules will conduct binary analysis with the fault error produced by the residual. The integration of these two modules is very hot in recent years[6]. On one hand, the dynamic characteristic of the fault signal produced by special faults depends mainly on the dynamic characteristics of the generator in the fault detection. On the other hand, the fault detection exerts great influence on the fault isolation. In order to accurately measure the fault, fault detection and fault isolation can't be separately considered. If we adopt the observer as fault detector, the observer gain matrix will greatly influence the dynamic characteristics of the residual generator. Hence, theoretically, the dynamic characteristics of fault signal sequence will also influenced by the gain impact of observer.

The design of interface adds more characteristics information of the fault signal on the basis of fault characteristic matrix (FSM) theory. This method deploys different fault feature matrixes: Bult attribute （$FSM01$）, fault residual sensitivity characteristic （FSM_s）, occurring sequence characteristics (FSM_o), and occurring time occurrence (FSM_o). Those matrixes store the information of impact of fault on residual set. The nest introduces the method of obtaining the above matrix by using the interval observer model.

FSM_s: evaluate the fault signal sensitivity and describe the degree of residual i exceeds the threshold caused by fault f_j within the interval shown in (19). Therefore, according to the internal form (26) of the threshold, FSM_s should be proportional to the residual sensitivity function $S_f(q^{-1})$ and inversely proportional to $\overline{r}_i^o(k)$ or $\underline{r}_i^o(k)$. The estimation formula of FSM_s is as follows:

$$FSM_S = \begin{cases} \dfrac{S_{ri,fj}(q^{-1})\eta(k-t_0)}{\left|\overline{r}_i^o(k)\right|}, if\ r_i^o(k) \geq 0\ and\ k \geq t_0 \\ \dfrac{S_{ri,fj}(q^{-1})\eta(k-t_0)}{\left|\underline{r}_i^o(k)\right|}, if\ r_i^o(k) < 0\ and\ k \geq t_0 \\ \qquad if\ \ k < t_0 \end{cases} \quad (27)$$

Wherein, $\eta(k)$ is step-input and $S_{ri,fj}(q^{-1})$ is the relative sensitivity of normal residual to fault f_j.

The consistency of the observed fault signal sequence $\phi_i(k)$ and the FSM_s of the theoretical fault j can be shown by f_s. There exists i that can make FSM_s zero. When $|\phi_i(k)| \geq 0.5$, $f_s = 0$. Otherwise, the expression of f_s is as follows:

$$f_s = \frac{|\sum_{i=1}^{ny}(\phi_i(k)FSM_s)|}{\sum_{i=1}^{ny}|FSM_s|} \quad (28)$$

The fault signal observed by sensitivity factor decides whether the final detection fault assumption establish or not. For example, Bult attribute:

$$FSM01 = \begin{cases} 1, FSM_s \neq 0 \\ 0, FSM_s = 0 \end{cases} \quad (29)$$

FSM_t: evaluate the occurring time of fault signal; in time of fault, the fault signal should appear at different times.

$$FSM_t = \begin{cases} [\varphi_{ij}, \overline{\varphi}_{ij}],\ \ if\ \ S_{ri,fj}(q^{-1}) \neq 0 \\ [-1,1],\ \ if\ \ \ S_{ri,fj}(q^{-1}) = 0 \end{cases} \quad (30)$$

The sequence of fault occurring:

$$FSM_O = \begin{cases} \sigma, \delta_j(\sigma) = \overline{\varphi}_{ij}\ \ and\ \ FSM_t \neq [-1,1] \\ \qquad 0, FSM_t = [-1,1] \end{cases} \quad (31)$$

δ_j is the non-repetitive $\underline{\varphi}_{ij}$ contained in row j in ascending order. Its value can't enable that be 1. Through the comparison of the observed information and stored matrix FSM, we can get the corresponding sensitivity factor $f01$, ft and fo of $FSM01, FSM_t$ and FSM_o. And then carry out weights summation on each sensitivity factor. In this way, we can predict the possibility of fault.

SIMULATIONS

The residual sensitively of the water level change sensor measurement parameters can be demonstrated as follows[8]:

$$\dot{x}(t) = a(t)x(t) + b(t)$$
$$y(t) = x(t) + p_y(t) \tag{32}$$

In the above formula:$x(t)$ refers to the input parameter of the sensor; $y(t)$ is the sensor output parameter;$p_y(t)$ stands for the measured interference noise signal; $a(t)$ and $b(t)$ are nonlinear function values of other measuring parameters; here we ignore their concrete forms; as functions a and b are uncertain, set $a = \hat{a} + \rho_a$ and $b = \hat{b} + \rho_b$. Here $\hat{a}$ and $\hat{b}$ are known nominal values.

The calculation algorithm of residue is composed of alarm condition and threshold value. If the residual is greater than the threshold value and the sensitive factor condition is met, it will produce an alarm.

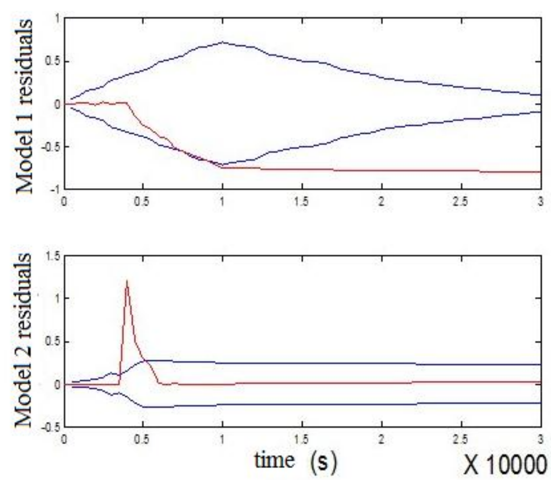

Figure 2 : Variation of residual and adaptive threshold with time

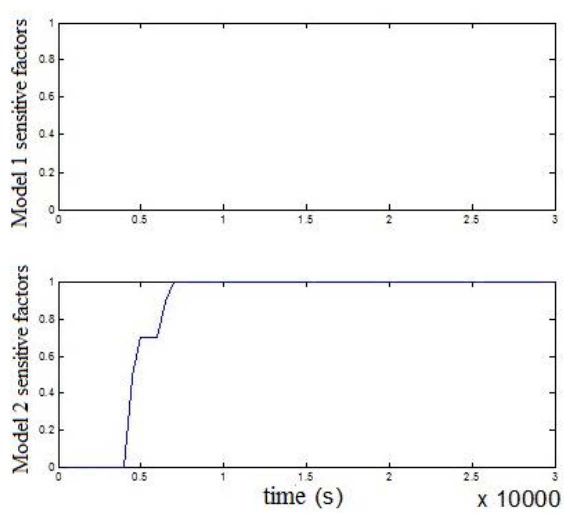

Figure 3 : Variation of sensitivity factor with time

When $t_0 = 4000s$, fault occurs in model 2. At that time, the gain of the observer in model 2 is adjusted to 0.5 while that of model 1 is adjusted 0.01. Diagram 2 shows residual of these two models and the corresponding adaptive residuals. According to the stored information of fault characteristic matrix, the fault of model 2 was first detected, but the detected fault signal will disappear over time. While the signal of model 1 is in line with the fault observed signal. In this kind of circumstance, the fault isolation method will take model 1 as the fault detection results. The application of traditional method may engender wrong choices. Diagram 3 shows the corresponding sensitivity of these two models. From the above, we can learn that the dynamic characteristics proved that model 2 has no fault despite the fact that the signal duration of it is not long.

CONCLUSIONS

This paper presents an optimal fault detection method for mine water level sensor. It makes up the shortcomings of the traditional method in fault detection, considers the dynamic nature of the fault signal, and then makes the correct judgment with the help of fault characteristic matrix. The application of this method to multi-fault and various sensor models would be the focus of future research.

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