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Fault diagnosis approach of hydraulic system using FARX model

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Abstract

A Fuzzy ARX (Fuzzy Auto-Regressive with eXtra inputs) model structure and corresponding fault feature extraction is studied and a fault feature extraction approach for the hydraulic system of construction machinery based on Fuzzy ARX model is proposed. Compared with classical ARX model, Fuzzy ARX model is capable to extract nonlinear features. On the basis of target fault features, FCM (Fuzzy Clustering Means) is served as fault classifier and the output of the FCM is the result of diagnosis. Several typical faults of hydraulic system were used to test the fault diagnosis approach. Experimental results show that all the test faults were correctly identified, and the fault diagnosis approach proved feasible and effective on construction machinery hydraulic system.

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Keywords: Hydraulic system, construction machinery, fault diagnosis, fuzzy logic, auto-regressive with extra outputs (ARX) model

1. Introduction

In order to meet the increasing demand of fast and efficient construction, mechanic and electric technology has been widely employed on the excavator. Hydraulic system is becoming more and more complex. Therefore, there is an important significance to develop an effective fault diagnosis approach for the excavator’s hydraulic system.

Faults in an excavator’s hydraulic system can take many forms, such as pump faults, valve faults, cylinder faults and so on. Hydraulic faults are generally sorted in several grades according to severity. Complete failures and abrupt faults are comparatively easy to detect. Fault detection techniques related to complete failures of control and equipment components of hydraulic system were proposed. Gradually

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generating faults are hard to detect early using limit-checking methods with simple residuals because fault effects are often masked by control actions. On the other hand, the hydraulic system is nonlinear with dynamic property. It is difficult to develop a fault feature extraction technique based on linear model[2,3]. Fuzzy ARX model has been proposed for the nonlinear process, which can effectively describe the nonlinear property of a process [4]. The fuzzy ARX model is valid for dealing with data from dynamic process. In this paper, an online fault feature extraction approach based on fuzzy ARX model was put forward. This approach was effectively applied on SWE50 excavator and could accurately diagnose faults.

2. Fault diagnosis approach

2.1. Structure of fuzzy ARX

Let us consider a single-input-single-output nonlinear system which can be configured as following fuzzy relational equations

$$\begin{aligned} &\underset{\sim}{R}^1:\ \text{IF } x \text{ is } \underset{\sim}{A}^1,\ \text{THEN } y \text{ is } \underset{\sim}{B}^1 \\ &\vdots \\ &\underset{\sim}{R}^r:\ \text{IF } x \text{ is } \underset{\sim}{A}^r,\ \text{THEN } y \text{ is } \underset{\sim}{B}^r \end{aligned} \tag{1}$$

The system can be described by a system of disjunctive rules, we could decompose the rules into a single aggregated fuzzy relational equation as follows

$$\begin{aligned} y = &\left(x \circ \underset{\sim}{R}^1\right) \text{AND} \left(x \circ \underset{\sim}{R}^2\right) \text{AND} \\ &\cdots \text{AND} \left(x \circ \underset{\sim}{R}^r\right) \end{aligned} \tag{2}$$

Or

$$y = x \circ \underset{\sim}{R}$$

where, $\underset{\sim}{R} = \underset{\sim}{R}^1 \cap \cdots \cap \underset{\sim}{R}^r$.

We can incorporate ARX model into fuzzy relational equations. The fuzzy ARX model can be written as following equations

$$\begin{aligned} &\underset{\sim}{B}^1:\ \text{IF } y(t-1) \text{ is } \underset{\sim}{B}^1,\ \text{THEN } y(t) = -a_1^1 y(t-1) - \cdots - a_{n_a}^1 y(t-n_a) \\ &+ b_1^1 u(t-1) + \cdots + b_{n_b}^1 u(t-n_b) + e^1(t) \\ &\vdots \\ &\underset{\sim}{B}^n:\ \text{IF } y(t-1) \text{ is } \underset{\sim}{B}^n,\ \text{THEN } y(t) = -a_1^n y(t-1) - \cdots - a_{n_a}^n y(t-n_a) \\ &+ b_1^n u(t-1) + \cdots + b_{n_b}^n u(t-n_b) + e^n(t) \end{aligned} \tag{3}$$

above equations can be represented in an aggregated fuzzy relational equation as follows

$$y(t) = \underset{\sim}{\mathbf{B}}^T\left(y(t-1)\right) \Theta \boldsymbol{\varphi}(t) + e(t) \tag{4}$$

where,

$$\boldsymbol{\varphi}(t)=\left[y(t-1),\cdots,y(t-n_a),\right.$$
$$\left.u(t-1),\cdots,u(t-n_b)\right]^T$$

$$\boldsymbol{\Theta}=\begin{bmatrix} a_1^1,\cdots,a_{n_a}^1,b_1^1,\cdots,b_{n_b}^1 \\ \vdots \\ a_1^n,\cdots,a_{n_a}^n,b_1^n,\cdots,b_{n_b}^n \end{bmatrix}=\begin{bmatrix} \boldsymbol{\theta}^1 \\ \vdots \\ \boldsymbol{\theta}^n \end{bmatrix}$$

$$\underset{\sim}{\mathbf{B}}\left(y(t-1)\right)=\left[\mu_{\underset{\sim}{B}^1}\left(y(t-1)\right),\cdots,\mu_{\underset{\sim}{B}^n}\left(y(t-1)\right)\right]^T$$

Then Equ. (4) could be simplified as follows

$$y(t)=\boldsymbol{\varphi}^T(t)\underset{\sim}{\boldsymbol{\theta}}+e(t) \tag{5}$$

where, $\underset{\sim}{\boldsymbol{\theta}}=\underset{\sim}{\mathbf{B}}^T\left(y(t-1)\right)\boldsymbol{\Theta}$.

2.2. Fault feature extraction approach

The fault feature extraction approach could be given as following steps:
(1) Define membership functions.
Five Gaussian membership functions were used to represent the output y as shown in Figure 2.

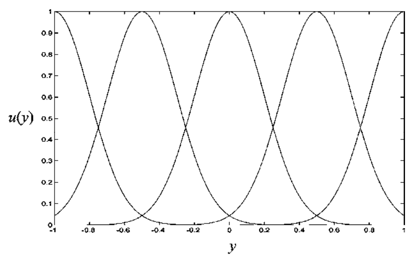

Figure 2. Memship function for the output y

(2) Define the fuzzy relational rules.
Fuzzy relational rules were consisted of five equations which can be given by

$$\begin{aligned} &\underset{\sim}{B}^1:\ \text{IF } y(t-1) \text{ is } \underset{\sim}{B}^1,\ \text{THEN } y(t)=-a_1^1y(t-1)-\cdots-a_{n_a}^1y(t-n_a) \\ &+b_1^1u(t-1)+\cdots+b_{n_b}^1u(t-n_b)+e^1(t) \\ &\vdots \\ &\underset{\sim}{B}^5:\ \text{IF } y(t-1) \text{ is } \underset{\sim}{B}^5,\ \text{THEN } y(t)=-a_1^5y(t-1)-\cdots-a_{n_a}^5y(t-n_a) \\ &+b_1^5u(t-1)+\cdots+b_{n_b}^5u(t-n_b)+e^5(t) \end{aligned} \tag{6}$$

(3) Establish the Fuzzy ARX model

We can establish a corresponding ARX model for each fuzzy rule. The parameters of fuzzy ARX model is estimated by applying the least square method and is given by

$$\hat{\boldsymbol{\theta}}^i = \left[\sum_{t=1}^{N} \left(\mu_{\underset{\sim}{B}^i} \left(y(t-1) \right) \right)^2 \boldsymbol{\varphi}(t) \boldsymbol{\varphi}^T(t) \right]^{-1} \sum_{t=1}^{N} \mu_{\underset{\sim}{B}^i} \left(y(t-1) \right) \boldsymbol{\varphi}(t) y(t) \tag{7}$$

and

$$\hat{\boldsymbol{\Theta}} = \begin{bmatrix} \hat{\boldsymbol{\theta}}^1 \\ \vdots \\ \hat{\boldsymbol{\theta}}^5 \end{bmatrix} \tag{8}$$

(4) Extract the fault feature vector

Generally, dimension of parameter matrix is so big that fault classifier can not properly determine the fault condition. To improve efficiency of fault diagnosis, we use weighted vector as the fault feature vector as follows

$$\mathbf{f} = \lambda_1 \hat{\boldsymbol{\theta}}^1 + \cdots + \lambda_5 \hat{\boldsymbol{\theta}}^5 \tag{9}$$

where, $\lambda_1 + \cdots + \lambda_5 = 1$.

3. Experiment

With the SWE50 experimental excavator, sample data is generated from three single fault cases including piston wear, spool stroke and spool wear. The observation vector at time t, which is composed of the variables from the simulation model, may be written as follows

$$x(t) = \left[P_P(t), P_A(t), P_B(t), Q_P(t) \right]^T$$

where P_P and Q_P are the pressure and the flow rate at pump outlet respectively. P_A and P_B are the pressure at port A and port B of valve respectively. The fuzzy ARX model can be rewritten as follows

$$\begin{cases} Q_P(t) = \mathrm{FARX1}\left(Q_P(t-1), Q_P(t-2), P_P(t-1), P_P(t-2) \right) \\ P_A(t) = \mathrm{FARX2}\left(P_A(t-1), P_A(t-2), P_B(t-1), P_B(t-2) \right) \end{cases}$$

With the SWE50 experimental excavator, sample data is generated from three target fault cases including normal, piston wear, spool stroke and spool wear.Several test faults were introduced to verify the classification performance of FCM clustering algorithm. A fault feature vector was incorporated into the dataset of target faults at a time. Then FCM clustering algorithm was used to classify the test fault. The classification result shows that all the test faults were correctly classified as shown in Table 2. The fault diagnosis using fuzzy ARX and FCM proves feasible and effective on excavator's hydraulic system.A SWE50 excavator was used to verify the online fault detection approach. Experimental results show that the proposed approach could be effectively applied to the fault extraction of the excavator's hydraulic system.

Table 2 Output of FCM fault classifier

No.	Target fault cases				Test sample	Output
	F0	F1	F2	F3		
(1)F0	0.842	0.000	0.598	0.188	0.966	F0
(2)F1	0.007	0.869	0.004	0.006	0.959	F1
(3)F1	0.007	0.746	0.001	0.005	0.952	F1
(4)F2	0.000	0.000	0.611	0.000	0.943	F2
(5)F2	0.258	0.000	0.745	0.006	0.920	F2
(6)F3	0.000	0.000	0.000	0.658	0.797	F3
(7)F3	0.000	0.000	0.001	0.520	0.894	F3

4. Conclusion

Aiming at the hydraulic system of excavator, a fault extraction approach using fuzzy ARX was put forward in this paper. With this approach, fuzzy ARX models were developed using sample data for target faults; Fault feature vector was extracted from the model; FCM clustering was used as the fault classifier to sort the test fault to the target faults. The hydraulic system of SWE50 excavator was developed to verify the fault detection approach. The proposed fault extraction approach was verified via this experimental excavator. Experimental results show that the proposed approach could be effectively applied to the fault detection of the excavator's hydraulic system.

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