퍼지논리를 이용한 다중관측자 구조 FDIS의 성능개선

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Performance Improvement of MOS type FDIS using Fuzzy Logic

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Abstract - A passive approach for enhancing fault detection and isolation performance of multiple observer based fault detection isolation schemes(FDIS) is proposed. The FDIS has a hierarchical framework to perform detection and isolation of faults of interest, and diagnosis of process faults. The decision unit comprises of a rule base and fuzzy inference engine and removes some difficulties of conventional decision unit which includes crisp logic and threshold values. Emphasis is placed on the design and evaluation methods of the diagnostic rule base. The suggested scheme is applied for the FDIS design for a DC motor driven centrifugal pump system.

1. Introduction

Automated large scale systems are characterized by an increase in desired level of system reliability. And achievement of the desired reliability becomes more difficult than ever. Among various methods to enhance system reliability, fault detection and isolation schemes(FDIS) can be considered to be the most promising. FDIS can be classified into many categories according to the type of process model, the method of residual generation and the diagnostic algorithm adopted in the scheme. According to the type of process model, the FDIS can be classified into the following groups:

(a) Analytic Redundancy Method (ARM) [1][2]
(b) Rule (Knowledge) based approaches [3]
(c) Techniques based on the data structure [4]

In the ARM group, there are two typical approaches: a) state estimation based and b) parameter estimation based [1][5]. Although more attention has been paid to the observer approach than to the parameter estimation approach, the practical applicability of the scheme is very restrictive due to following well-known reasons. First, observer schemes require an exact mathematical model of the process to be diagnosed. Second, the FDI schemes fail to provide reasonable decisions when some uncertainties, such as unmodelled dynamics, or unknown external disturbances are introduced. Two major approaches, active and passive, have been developed to remove these difficulties. The active approach is to design a residual generator which is insensitive to modelling errors and disturbances while sensitive to the fault of interest.[6] The passive approach includes the use of adaptive thresholds and the design of more reliable decision logic unit using artificial intelligence tools such as fuzzy logic and artificial neural networks[7], and the approach is useful whenever the robust design of the residual generator is impossible.

In this paper, a new concept of decision logic design for MOS is suggested. The decision logic unit has a hierarchical framework to perform fault detection, isolation of faults, failed sensor identification, and diagnosis of process faults. The proposed scheme employs a fuzzy rule base and fuzzy inference engine and doesn't require threshold values. One of important contribution of this paper is the suggestion of the design and evaluation method of the diagnostic rule base. The design concepts are applied to the design of a multiple observer based FDIS for a DC motor driven centrifugal pump system.

2. Residual Generation for MOS type FDIS

The residuals contain the information that will be used directly for fault detection and diagnosis. The quality of the information carried by the residuals influences the diagnostic performance. In order to define and explain the residuals, we consider the dedicated observer scheme(DOS) in which conventional observer theory is adopted. we also assume a linear process model for brevity.

$$\begin{aligned} \dot{x}(t) &= Ax(t)+Bu(t)+Df(t) \\ y_i(t) &= C_i x(t)+E_i f(t)\ ,\ i=1,2,..p \end{aligned} \tag{1}$$

where $f(t)$ is fault vector. Assume that the system is observable from each measurement y_i. Then p dedicated observers can be constructed in the following form:

$$\begin{aligned} \dot{\hat{x}}^k &= (A-L_kC_k)\,\hat{x}^k + L_k y_k + Bu \\ \hat{y}_i^{\,k} &= C_i\,\hat{x}^k \qquad (i,k=1,2...p) \end{aligned} \tag{2}$$

Residuals can be defined in various ways since the dedicated observer bank provides redundant information. Two typical residuals are defined as

$$R_{jk}=y_j-\ \hat{y}_j^{\,k}\ ,\ j,k=1,2,\cdots,p \tag{3}$$

$$RE_i^{jk}=|\ \hat{x}_i^{\,j}-\ \hat{x}_i^{\,k}|\ ,(i=1,2,..n\ ;\ j,k=1,2,..p)\ (j\neq k) \tag{4}$$

where $\hat{x}_i^{\,j}$ is the estimate of x_i from the jth observer. Some function of residuals may be chosen as the condition variables. In order to design more reliable decision rules, following residuals are defined.

$$RT_{jk} = \sum_{i=1}^{n} RE_i^{jk} \quad (5)$$

where RT_{jk} gives the total difference between the estimated vectors provided by the i th observer and the k th observer. The total number of residuals RT_{ij} is limited to p(p-1)/2.

3. Design and evaluation criterion for the rule-base

3.1 Decision rules for sensor faults

Once the condition variables were selected, detection isolation rule-base is readily obtained in general.

Detection and Localization Rules:
If(RT_{12}=PO or RT_{23}=PO or .... or R_{p1}=PO), Then fault
If(RT_{12}=PO & RT_{23}=PO & ... & RT_{p1}=PO),
Then process fault
Otherwise, sensor fault

Rules for identification of a failed sensor:
The residuals RT_{ij} can also be employed for the identification of a failed sensor. The identification rules are obtained in a logical way. Let us assume an ith sensor fault. Then, the residuals RT_{ij} and RT_{ki} have non-zero values, while other residuals have zero values.

Rule 1 : If(RT_{12},RT_{23},.....,RT_{p1})=(PO,AZ,AZ,.....,PO),
Then sensor 1 fault

Rule p : If(RT_{12},RT_{23},.....,RT_{p1})=(AZ,.....,AZ,PO,PO),
Then sensor p fault

Unfortunately, there is no logical way to design rule-base for process fault detection. An evaluation criterion which helps the design of rule-base based on the analysis of fault data, is described in next subsection.

3.2 Evaluation criterion for the rule-base design

The rule-base is at the core of the proposed FDIS and determines the performance of the FDIS. To design an effective rule-base and an inference engine, the following design procedure can be employed.

Step 1: Fault data collection and analysis
Step 3: Add expert and theoretic knowledge
Step 4: Select condition variables in the rules
Step 5: Build fuzzy-subsets for the selected variables
Step 6: Select fuzzy composition operator

In all MOSs, observers provides excessive redundant information, and there is some degree of freedom in the selection of condition variables, which leads to different rule-bases. So, we need a criterion by which the quality of the linguistic rule-base can be evaluated. To suggest an evaluation criterion, let us make following definitions.

Definition 1. [Distance between two terms] :
For a fuzzy variable X with term set or linguistic values $[v_1\ v_2\ ....\ v_{ip}]$ the distance between two terms is defined as

$$d_X(v_i\ , v_j) = |\ i-j\ | \quad (6)$$

Definition 2. [Distance between two rules] :
Consider two rules with same condition variables $[\ x_1\ x_2\ ....\ x_n\ ]$where each fuzzy variable, x_i, has term set $[\ v_{i1}\ v_{i2} \cdots v_{ip}\ ]$. Assume following two rules.

Rule i: If $(x_1\ is\ v_{1i}) \wedge (x_2\ is\ v_{2i}) \wedge ..\ .(x_n\ is\ v_{ni})$, Fault i
Rule j: If $(x_1\ is\ v_{1j}) \wedge (x_2\ is\ v_{2j}) \wedge ..\ .(x_n\ is\ v_{nj})$, Fault j

The distance between two rules is defined as:

$$D_{ij} = \sum_{k=1}^{n} d_{X_k}(v_{ki}, v_{kj}) \quad (7)$$

The distance is a measure of distinguishability of two faults, Fault i and Fault j, when two rules, Rule i and Rule j, are employed.

Definition 3. [Score of a rule]:
The score of the Rule i in a rule-base is defined as the sum of the distances from Rule i to each other rule:

$$S_i = \sum_j D_{ij}\ ,\ j \neq i \quad (8)$$

Definition 4. [Score of a rule-base]:
The score of a rule-base is defined as the sum of all the distances between every two rules in the rule-base.

$$S_{RBk} = \sum_i \sum_j D_{ij} \quad (9)$$

The distance and the score have following properties.

- The addition of a significant condition variable increases the distance between a rule pair and the score of the rule-base. and the converse is also true.
- High score implies improved distinguishability and low score means conflict.
- Distance between terms is defined for a variable, not for different variables.

Quality of a rule-base is a relative concept, so the evaluation of a given rule-base is performed as follows:

Step 1. For every rule pair, calculate the distances D_{ij} for all i and j.
Step 2. For every rule, calculate the score of the rule S_i.
Step 3. Calculate the score of the kth rule-base S_{RB_k}.
Step 4. Compare S_i , S_{RB_k} with those of other rule-base that is obtained from the same data.

For illustration, consider the following two rule-bases in table 1 that are built from a set of fault data. Our problem is to determine which rule-base is better. It is assumed that the premises in each rule are connected with 'and' operator.

Evaluation of those rule-bases starts by calculating distance D_{ij}. Let us assume that the term set of each residual is chosen as {NB, NS, AZ, PS, PB}. Two distance Maps in table 2 are generated.

Table 1. Rule-Base[1] Rule-Base[2]

Rule NO.	R_{12}	R_{31}	R_{32}	R_{12}	R_{23}	R_{31}	Fault NO.
1	AZ	PS	NB	NS	AZ	PS	1
2	AZ	NS	PB	PS	AZ	NS	2
3	NS	PB	PB	AZ	AZ	PB	3
4	PS	NB	NB	AZ	AZ	NB	4
5	PS	PB	PB	AZ	PB	PB	5

Table 2. Distance maps for rule-base 1 and 2

Rule-Base[1]

Rule NO.	2	3	4	5
1	6	6	4	6
2	x	4	6	4
3	x	x	10	3
4	x	x	x	8

Rule-Base[2]

Rule NO.	2	3	4	5
1	4	2	4	4
2	x	4	2	4
3	x	x	4	2
4	x	x	x	6

If there is a zero entry, it means that the corresponding two faults cannot be isolated. In such cases, the condition variables must be changed or added to produce nonzero distances. If there is no zero entry, find the score of the rule-base. In this example, the score of the rule-base 1 is 57, and that of rule-base 2 is 36. So, it can be concluded that rule-base 1 is superior to rule-base 2 in their diagnostic ability.

In rule-base 2, there may be some conflicts between Fault 1 and 3, Fault 2 and 4, and Fault 3 and 5, since they got the minimum score. rule-base 1 reduces the number and the degree of expected conflicts. It is noteworthy that the evaluation criterion indicates the diagnostic ability of the given rule-base, provides an useful selection criterion of condition variables and the degree of usefulness of each condition variable.

4. An application to a DC motor driven pump system

4.1 A motor-pump system

The proposed FDIS is applied to a DC motor driven centrifugal pump system. Such motor-pump systems are widely used for the transportation of all kinds of liquids. The state variables and the measurement outputs are defined as

$$x^T = [\Delta I_a(t)\ \Delta w(t)\ \Delta \dot{M}(t)] \tag{10}$$

where x_1 is the armature current of the motor, x_2 is the angular velocity of the motor-pump shaft, and x_3 is the mass flow rate of the fluid. The linear model is taken from [8]. In Table 3, the relations between the faults and the corresponding process parameter variations are defined. These relations are taken from Isermann [9].

Table 3. Faults and paramemter variations

Fault1:brush fault	>Armature Resistance increase.
Fault2: Short circuit of armature coil.	>Armature Resistance (Ra) decrease. >Armature Inductance (La) decrease.
Fault3: Excess of lubrication oil on ball-bearing.	>Adhesive Friction (Cf) decrease. >Pump Torque (Kp) decrease.
Fault4: Dirt on ball-bearing.	>Adhesive Friction (Cf) increase. >Pump Torque (Kp) decrease.
Fault5:Impeller degradation	>Fluid Resistances (Ar) increase. >Pump Cha. coef (Hp) decrease. >Pump-Torque-coef(Kp) decrease.

4.2 Rule-Base of the FDIS

The rule-base includes; a rule-base for sensor faults, a rule-base for process faults, and the rules for localizing sensor fault and process fault. Detection itself is very simple because any non-zero RT indicates a fault. Rule sets for isolation of sensor faults and process faults are obtained separately and combined together to form a complete rule-base given in table 4.. Because of the large number of faults to be detected and isolated, residual R_{ij}s, together with RT_{ik} . are chosen to form the rule-base.

Table 4. A rule-base for Hierarchical FDIS

Detection	IF(RT_{12}=PO or RT_{23}=PO or RT_{31}=PO). THEN fault
Failed sensor Identification & Isolation of sensor fault/ process fault	RS1: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(PB,PM,AZ,PM), Then SF1 RS2: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(AZ,PB,PB,AZ), Then SF2 RS3: IF($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(AZ,AZ,PM,PM), Then SF3 RP : If($\lvert R_{31}\rvert$,RT_{12},RT_{23},RT_{31})=(PS,PM,PM,PS) OR (PB,AZ, PM, PM). Then Process fault
Process fault Diagnosis	RP1: IF(R_{12},R_{23},R_{31}) =(NS,AZ,PS), Then PF 1 RP2: IF(R_{12},R_{23},R_{31}) =(PS,AZ,NS), Then PF 2 RP3: IF(R_{12},R_{23},R_{31}) =(AZ,AZ,PB), Then PF 3 RP4: IF(R_{12},R_{23},R_{31}) =(AZ,AZ,NB), Then PF 4 RP5: IF(R_{12},R_{23},R_{31}) =(AZ,PB,PB), Then PF 5

4.3 Simulation study

Three observers with the eigenvalues (-60, -50,-40) are designed for residual generation and fuzzy subsets of each selected condition variables are defined as shown in Table 5.

Table 5. Linguistic values and membership functions

Res	Linguistic Values and Membership Functions
R_{12}	NB(-3.7 -0.3], NS[-1.4 -0.3 0.0], AZ[-0.05 0 0.05], PS[0.0 0.3 1.4], PB[0.3 3.7)
R_{23}	NM(-0.42 -0.1], AZ[-0.2 0 0.2], PM[0.1 0.42)
R_{31},	(NB(-2.3 -0.05], NS[-1.0 -0.15 0], AZ[-0.15 0 0.15], PS[0.0 0.15 1.0], PB[0.05 2.3))
$\lvert R_{31}\rvert$	(AZ[0.0 0.15], PS[0.0 0.15 1.0], PB[0.05 2.3))
RT_{12}	AZ[0.0 2.0], PM[0.3 2.7 22.0] , PB[2.7 35.0)
RT_{23}	AZ[0.0 1.2], PM[0.1 2.5 10 18], PB[2.5 31.0)
RT_{31}	AZ[0.0 0.15], PS[0.05 0.45 1.45], PM[0.1 2.0 7.5], PB[1.0 11.0)

One-sided and two-sided triangular membership functions and trapzoidal form membership function are employed. They are distinguished by the number of representative points. The notation '(' or ')' represent the open-tail membership function which has membership value '1' for all input values 'smaller' or 'larger' than the number specified as left argument or right argument. Mamdani's Max-Min operator is employed for the fuzzy inference.

In the simulation, an input $\Delta u = 10$[V] is applied to the motor-pump system. The pump coefficient (H_p) is varied from 95 percent to 105 percent of its nominal value to verify the robust property of the FDIS against parameter variations. It is assumed that the variation is represented by the equation, $Hp = Hp_n(1+0.05\sin(100t))$ where Hp_n is nominal parameter value, and that each fault occurs at 20 second. Tables 6. shows the diagnostic results in grade of membership(a time average) for a 5% fault.

Table 6. Diagnostic performance for 5% faults

Fault	Detection Time	Membership Value	Competition(Max-membership)
PF 1	20.57	0.22	NO
PF 2	20.72	0.25	NO
PF 3	21.24	0.22	PF1 (0.02)
PF 4	21.27	0.23	PF2 (0.02)
PF 5	21.36	0.20	PF3 (0.09)
SF 1	21.52	0.09	NO
SF 2	21.08	0.28	NO
SF 3	20.46	0.09	NO

The detection time is defined as the time instant that the membership grade of the fault exceeds the α-cut level which is selected as 0.03 in all simulations. The membership value which is the output of the inference engine of the FDI subsystem, usually means the possibility of the fault and the compatibility of the observed data with the premise of corresponding rule. An important aspect of the proposed FDI subsystem is that the scheme allows the competition among all possible faults. In the simulation study, three competitions were reported; PF3-PF1, PF2-PF4 and PF5-PF3, where the left is the true fault. It should be noticed that an assumption, that the maximum degree of fault should be limited to the 30% variation of corresponding parameters, has been made for this development. It means that our concern is the detection of incipient fault. Although the FDI subsystem was designed based on the fault data for the range of 5% to 30%, the subsystem works very well even for 50% or larger magnitude of faults.

5. Conclusions

In this paper, a MOS type FDIS is proposed and applied to a DC motor driven centrifugal pump system. The FDIS removes the difficulties of conventional MOS because it doesn't require threshold values, and provides reasonable decisions even in an uncertain environment. The design and evaluation of diagnostic rule-base is illustrated and a new evaluation method with which the quality of rule-base can be evaluated, is suggested. The application of this evaluation criterion to the selection of condition variables and diagnostic rules is described. In contrast to the conventional ARM based FDI schemes, it is always possible to introduce human knowledge in the design stage and external information that cannot be represented in terms of state variables may be included in the rule-base. It is noteworthy that there is a strong relationship between the severity of a fault and the membership grade. The design concepts are applied to a DC motor driven centrifugal pump system.

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