Fault Diagnosis with Dynamic Fuzzy Discrete Event System Approach

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Abstract. Determining faults is a challenging task in complex systems. A discrete event system (DES) or a fuzzy discrete event system (FDES) approach with a fuzzy rule-base may resolve the ambiguity in a fault diagnosis problem especially in the case of multiple faults. In this study, an FDES approach with a fuzzy rule-base is used as a means of indicating the degree and priority of faults, especially in the case of multiple faults**.** The fuzzy rule-base is constructed using event-fault relations. Fuzzy events occurring any time with different membership degrees are obtained using k-means clustering algorithm. The fuzzy sub-event sequences are used to construct super events. The study is concluded by giving some examples about the distinguishability of fault types (parameter, actuator) in an unmanned small helicopter.

1 Introduction

Today, fault detection and diagnosis are very important tasks in complex systems. There are two main approaches to a fault detection and diagnosis (FDD) problem: model based [1], [2], [17] and knowledge based [3]. A summary of these approaches is given in Willsky [1] and their developments are summarized by Isermann [2]. The extension of knowledge-based approaches (i.e., neural networks, adaptive neural networks, neuro-fuzzy systems and hybrid neuro-fuzzy systems) and design methodologies can be seen in [3], [18] and [19].

The chosen diagnosis method is important to isolate multiple faults in complex systems. If no information is available on the fault-event relation, classification methods (i.e., fuzzy clustering, artificial neural network and probabilistic methods) can be used for fault diagnosis. If more information about event-fault relations is available, different methods of reasoning (i.e., probabilistic reasoning, probabilistic reasoning with fuzzy logic and reasoning with artificial intelligence [21], [22], [24]) can be applied. When fuzzy reasoning is utilized, it is possible to present the results in the form of possibility of faults and their sizes [23]. The adaptive neuro-fuzzy systems can be used in order to improve the rule-base further [3], [18].

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Conventional DES approaches [7], [16] are used to model systems that cannot be described by differential equations or difference equations, but must be described by sequences of events that record significant qualitative changes in the state of the system. Although they have been applied in many engineering fields, they may not be adequate for fault diagnosis applications, in which the state (e.g., a component health status) is somewhat uncertain (e.g., degree of fault) and vague even in a deterministic sense [18], [19]. Furthermore, the determination of the faulty component's set could be too restrictive since users may want to identify different levels of faults. Usually, the state (healthy or unhealthy) of components, obtained from measurements, expert experience, or analysis using probabilistic schemes cannot be determined accurately. The research on the diagnostic problem for such systems with fuzziness is interesting and important. Furthermore, the transition from one state to another is also vague. It is hard to say how exactly an actuator's condition has changed from "good" to "bad".

Recently, the failure diagnosis problem has been investigated via DES approach [7]. Two basic practices for this purpose are automata theory and Petri nets. Some modeling practices using the above theories can be found in [7] and [8]. Sometimes one may need to model systems that cannot be modeled by the current DES modeling methods due to the vagueness in the definitions of the states and/or events. In order to overcome these difficulties, the concepts of fuzzy state and fuzzy event can be used [9], [10]. Lin and Ying [12] initiated the study of FDES by combining fuzzy set theory with DES to solve problems, which are not possible to be solved by conventional DES. They then applied their results about FDES on HIV/AIDS treatment planning problem [25].

In this study to solve the fault diagnosis problem, an FDES approach based on fuzzy rule-base (i.e., same other fuzzy reasoning methods) is proposed. The proposed approach then has been applied to a failure diagnosis problem in an unmanned small helicopter. In literature one can find many fault diagnosis methods about helicopters. Among them [5], [13], [20] are focused on detecting and identifying helicopter (CH-46) gearbox faults. Signal analysis techniques with pattern classification (Kalman filter approach [6], decision trees, learning vector quantization, multi-layer perceptrons, fuzzy ARTMAP, and Gaussian mixtures [20]) are used to diagnose helicopter gearbox faults. Feature vectors used to isolate helicopter faults are based on neuro-fuzzy system, reasoning [15] and signal processing approaches [13], [20] (Mean square RMS, kurtosis maximization). Two studies related to the actuator fault compensation and actuator and sensor faults in a helicopter can be seen in [14] and [6], respectively. Multiple faults also may occur in a helicopter at the same time. Hence, the FDES concept is more convenient in the investigation of this problem. It also allows one to first build each component model separately. Moreover, to construct features (events-fault relations) the k-means classification algorithm can be used since it is simple. In the literature there are a few FDD applications employing DES [7] but no FDES based application, so far.

The rest of the paper is organized as follows. In section 2, DES and FDES concepts are given. In section 3, a case study is introduced. In section 4, the results obtained are presented. Finally, in the last section, a summary of the present work and some conclusions and future studies are indicated.

2 Fuzzy Discrete Event Systems

State, event and event transition function values are crisp in a DES. Before an FDES structure is modelled, let's recall a model for a DES structure first.

Definition 1: Discrete event systems can be modeled by a five-tuple $G = (Q, \Sigma, f, h, q_0)$ [11], where

- Q is the set of states,
- Σ is the set of events containing detectable (i.e., an event is *detectable* if it produces a measurable change in the output) and undetectable events, which are generally fired asynchronously,
- $f : Q \text{ x } \Sigma \rightarrow Q$ is the state transition function,
- $h : Q \times \Sigma \rightarrow \hat{\Sigma}$ is the output equation, where $\hat{\Sigma}$ is a set of detectable events, $\hat{\Sigma} \subseteq \Sigma$,
- q_0 is a $1 \times n$ (n: the number of places) initial state vector, whose elements are zero or 1.

In order to generalize a DES structure into an FDES structure, the concepts of *fuzzy state* and *event* are proposed in this study. We combine fuzzy set theory with (crisp) DES structure in which events and states have crisp values. In an FDES structure, events and state transition functions are fuzzy vectors whose components take values between zero and 1. All the events in FDES occur continuously at the same time with different membership degrees (i.e., events firing at the same time with different degrees); hence the system can be in many places (states) at a given instant.

If we reformulate the crisp DES into fuzzy DES we may write below the definition for FDES as given in [12].

Definition 2: Fuzzy discrete event systems can be modeled by a five-tuple $G = (\overline{Q}, \overline{\Sigma}, \bar{f}, \bar{h}, \bar{q}_0)$ where,

- $\overline{Q}$ is the set of states $(q_1 ... q_n)$, which occur continuously with different membership degree ($\mu_{q_1}(t) ... \mu_{q_n}(t)$) at an instant of time, where n is the number of states,
- $\overline{\Sigma}$ is the set of events $\left(e_1 ... e_m\right)$ containing detectable and undetectable events, all events occurs continuously with different membership degrees, ($\mu_{e_1}(t) ... \mu_{e_m}(t)$) at an instant of time, where m is the number of events,
- $\bar{f} : \overline{Q}\,[0,\ T] \text{ x } \overline{\Sigma}\,[0,\ T] \rightarrow \overline{Q}$ is the state transition function ,
- $\bar{h} : \overline{Q} \times \overline{\Sigma} \rightarrow \hat{\Sigma}$ is the output equation, where $\hat{\Sigma}$ is a set of detectable events, $\hat{\Sigma} \subseteq \overline{\Sigma}$
- $\bar{q}_0$ is the initial state vector showing the initial membership degrees of a system states.

In definition 2, the state transition function can be defined as a matrix called the state transition matrix whose components take values between zero and 1. Moreover, the number of the state transition matrices is equal to the number of events considered in a system.

3 Fault Detection and Identification (FDI) Method

The FDES approach is applied to detect and diagnose multiple faults in an unmanned small helicopter. The continuous-time 6 degrees of freedom linear model of a helicopter can be described by the following dynamical state equations [4], [14]:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{1}$$

The state variable vector x (dimension 9) is defined as:

$$x = [u \quad v \quad w \quad p \quad q \quad r \quad \varphi \quad \theta \quad \psi]^T \tag{2}$$

where u, v and w represents the longitudinal, lateral and vertical velocity (ft/sec), respectively; p, q and r represents the roll, pitch and yaw rates (rad/sec) respectively; φ, θ represent the roll and pitch attitude (rad); and ψ is the heading (rad). There are five control inputs i.e., $u = [u_1 \quad u_2 \quad u_3 \quad u_4 \quad u_5]^T$ where u_1 is the lateral stick (inch), u_2 is the longitudinal stick (inch), u_3 is the collective stick (inch), u_4 is the pedal position (inch) and u_5 is the horizontal tail incidence (degree).

3.1 Fuzzy FDI Method

In order to perform fuzzy FDI method in an efficient way we should take into account all possible fault types occurring in an unmanned small helicopter, which means that the database to be constructed will (hopefully) contain all possible fault types (i.e., those faults that will not prevent the helicopter to continue its execution). The proposed FDI method consists of 2 stages: off-line rule extraction and on-line fault detection and identification.

3.1.1 Off-Line Rule Extraction

Fig. 1 shows off-line rule extraction procedure. The system's fault model (i.e., system model including faults) and healthy model is used together to generate residuals. The k-means algorithm is applied to classify the residuals (the system parameters or some variables related to stick or percentage actuator faults are changed in a simulation program within 1 second time interval).

Many simulations have been performed to decide the number of the class centers. After examining the relation between the obtained cost value and used class centers in the k-means classification algorithm, 101 centers (classes) are chosen. These centers are called sub-events and used as rules' antecedent parts. To fuzzify sub-events, triangular and trapezoidal membership functions (or others) are used. Rules' antecedent parts

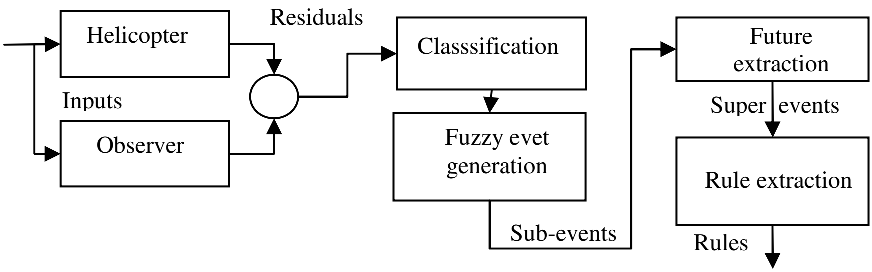

Fig. 1. Off-line rule extraction procedure

contain 20 sub-events (an event sequence). These event sequences are called feature vectors (super events). These super events are related to single, double and triple faults. The rule-base consists of 118 rules (the data base employed includes 118 different fault types). Super event table will not be presented here.

3.1.2 Off-Line Rule Extraction

Fig.2 shows on-line FDES based FDI procedure. There are 6 sensors that measure helicopter body speeds (*u, v*, and *w*) and angular velocities (*p, q*, and *r*) on real time. We used these sensor outputs to obtain residuals. In this study, two types of actuator faults called percentage and stuck actuator faults are created and used in the FDI algorithm. In our approach all events occur at the same time with different membership degrees. The sub-events membership degrees are calculated using Euclidean distance measure (the distance of measurement vectors to the predetermined class centers). Next, those, which are too small, are set to zero membership degree. The remaining sub-events are normalized among themselves. The super event generator labels residuals as sub-events and create a super event (an event sequence) by taking past 20 sub-events in time period. The membership degrees of super events are also calculated in this part. Super event membership degrees are calculated as follows: first, the last 20 (length is the same as super events) sub-event (taking place in the related super events) membership degrees are multiplied with each other. Next, those, which are too small, are set to zero membership degree. The remaining super events are normalized among themselves. The super events have a

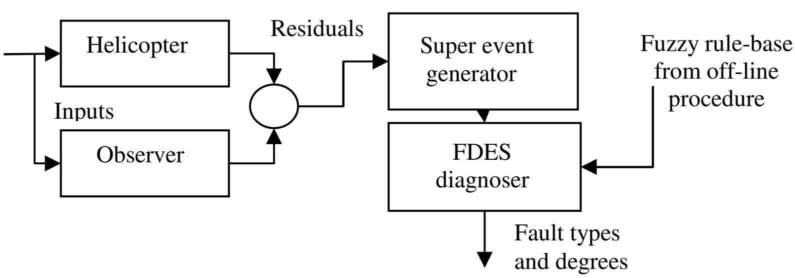

Fig. 2. On-line FDI procedure

dynamic structure; their membership degrees change at any time. These events are applied to the FDES diagnoser as inputs. The FDES diagnoser is constructed containing 12 fuzzy places (places show the system's faulty components related to 4 different parameters and actuators) based on rules derived using k means classification technique in off-line stage. They isolate faults and also give information about the percentage of the occurred fault types. The rule structure is given by

$$\mathbf{R^i}\mathbf{: IF}\ e_t \ldots e_{t-N} \text{ is } A^i_1\ \mathbf{THEN}\ (q_1 \text{ is } C^i_1, \ldots, q_m \text{ is } C^i_m),\ i=1,2,\ldots,n \tag{3}$$

Here, N is the integer related to the model order and, $e_t \ldots e_{t-N}$ denote the past input vector related to the sub-events, $q_1 \ldots q_m$, show states A^i_1 and $C^i_1 \ldots C^i_m$ are linguistic values (labels) represented as fuzzy subsets of the respective universes of discourse. The diagnoser outputs are degrees of failure (fault percentage) related to the faulty components. This is accomplished by using the COA defuzzification.

4 Simulation Results

There are many system parameters in a helicopter but we dealt with only four of them. These parameters are numbered as 1, 2, 3 and 4. The parameters 1 and 2 are related to the helicopter wings and 3 and 4 are related to the helicopter main rotor and tail rotor blade. Parameter faults are restricted to percentage faults.

There are four actuators in the helicopter. All of the actuators are taken into account for fault diagnosis. There are two types of faults in the actuators. The first one is percentage fault and the other is stuck fault. Both of these fault types are considered for fault diagnosis.

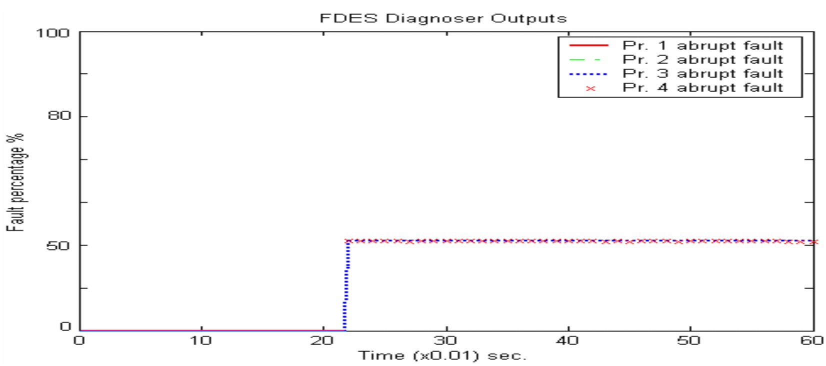

Fig. 3. Results obtained for the fault scenario I

The overall FDES based FDD method is tested on two different scenarios using a simulation program. In the first scenario, we created abrupt faults. There is no fault between 0 and 0.02 second. 50 % abrupt faults in parameters 3 and 4 (i.e paramaters related to the helicopter main rotor blades) are created at time 0.02 second. Figure 3 shows simulation result obtained by using the FDES diagnoser.

In the second scenario, again multiple faults are created. There is no fault between 0 and 0.02 seconds. 50 % abrupt faults in parameters 3 and 4, and 50 % stuck fault in actuator 1 (i.e., actuator begins to work normally, at the instant *t*; it sticks and remains at working condition of time *t*) are created at time 0.02 second. Figure 4 shows simulation result obtained by using the FDES diagnoser.

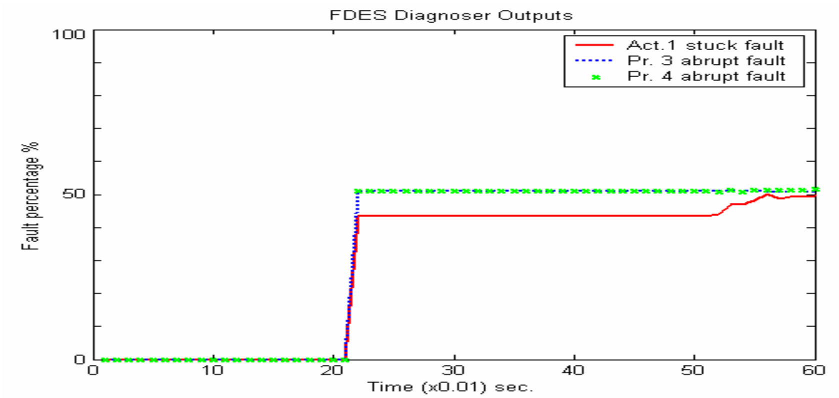

Fig. 4. Results obtained for the fault scenario II

5 Conclusion and Future Work

In this paper, a fuzzy rule based FDES approach to solve FDI problem is introduced and used in a logical way towards distinguishing multiple faults in an unmanned small helicopter. The fuzzy rule-base employed is constructed using event-fault relations. The fuzzy events are obtained using k-means clustering algorithm. Actually, the dynamic aspects of the fault diagnosis depends on the definition of “fault” events; if those events are based on time histories, then the resultant FDES is automatically a dynamical system. We are planning to tune the membership function parameters using a performance function with a genetic algorithm to improve FDI algorithm performance (fault isolation capability). Additionally, more advanced or complicated event definitions are being investigated to distinguish faults better. We believe that the approach introduced in this study will show researchers a new way to cope with the FDI problem in complex systems.

References

1. Willsky, A.S.: A survey of design methods for failure detection systems. Automatica, vol.12. (1976) 601-611
2. Isermann, R.: Supervision, fault-detection and fault diagnosis methods-an introduction. Control Eng. Practice, vol. 5 no. 5 (1997) 639– 652
3. Ayoubi, M., Isermann, R.: Neuro-fuzzy systems for diagnosis. Fuzzy Sets and Systems, 89 (1997) 289-307

4. Karasu, Ç.: Small-sized unmanned model helicopter guidance and control. M.Sc. thesis, Middle East Technical University Ankara Turkey November (2004)
5. Vinay, B., et al.: Diagnosis of helicopter gearboxes using structure-based networks. Proc.of the American Control Conference, Seattle Washington June (1995) 1623-1627
6. Constantino, R., et al.: Failure detection and identification and fault tolerant control using the IMM-KF with applications to the Eagle-Eye UAV. Proceedings of the 37th IEEE Conference on Decision & Control, Tampa Florida USA December (1998) 4208-4213
7. Sampath, M., et al: Failure diagnosis using discrete event models. IEEE Trans. on CST., vol.4. no.2. (1996) 105-124
8. Prock, J.: A new technique for fault detection using Petri nets. Automatica, vol. 27. no. 2. (1991) 239-245
9. Zadeh, L.A.: Fuzzy sets. Inform. Control, vol. 8. (1965) 338-353
10. Santos E.S.: Max-min automata, Inform. Control, vol.13. (1968) 363-377
11. Passino, K.M., Yurkovich, S.: Fuzzy Control. Addison Wesley Longman Inc, (1998)
12. Lin, F., Ying H.: Modelling and control of fuzzy discrete event systems. IEEE Trans. on Syst. Man and Cybernetics, vol. 32. no. 4. August (2002) 408-415
13. Wang, W.: Identification of gear mesh signals by Kurtosis maximisation and its application to CH46 helicopter gearbox data. Proceeding of the 11th IEEE signal processing workshop on statistical signal processing, 6-8 August (2001) 369-372
14. Yu, X.H.: Actuator fault compensation for a helicopter model. Proceedings of IEEE Conference on Control Applications, vol. 1. 23-25 June (2003) 1372-1374
15. Amulya, K., et al.: Hybrid reasoning for prognostic learning in CBM sytems. IEEE Aerospace Conference Proceedings, vol. 6. 10-17 March (2001) 2957-2969
16. Cassandrass, C.G., Lafortune, S.: Introduction to Discrete Event Systems. Boston MA: Kluwer (1999)
17. Isermann, R., Ballĕ, P.: Trends in the application of model-based fault detection and diagnosis of technical processes. Control Eng. Practice, vol. 5. no. 5. (1997) 709–719
18. Fuessel, D., Isermann, R.: Hierarchical motor diagnosis utilizing structural knowledge and self-learning neuro-fuzzy scheme. IEEE Trans. on Industrial Electronics, vol. 47. no. 5. October (2000)
19. Isermann, R.: On fuzzy logic applications for automatic control, supervision and fault diagnosis, IEEE Trans. on Systems, Man and Cybernetics – Part A: Systems and Humans, vol. 28. no. 2. March (1998) 221-235
20. Wen, F., Deb S.: Signal processing and fault detection with application to CH-46 helicopter data. IEEE Aerospace Conference Proceedings, vol. 6. 18-25 March (2000) 15-26
21. Dubois, D., Prade, H.: Fuzzy set-based methods in instance-based reasoning. IEEE Trans. on Fuzzy Systems, vol. 10. no. 3. June (2002) 322-332
22. Cayrac, D., Dubois, D., Prade, H.: Handling uncertainty with possibility theory and fuzzy sets in a satellite fault diagnosis application. IEEE Trans. on Fuzzy Systems, vol. 4. no. 3. August (1996) 251-269
23. Ulieru, M.: Fuzzy logic in diagnostic decision: Probabilistic networks. Ph.D. dissertation, Technical University of Darmstadt Germany (1996)
24. Wang, H., et al.: A framework of fuzzy diagnosis. IEEE Trans. on Knowledge and Data Eng., vol. 16. no. 12. December (2004) 1571-1582
25. Ying, H., et al.: A fuzzy discrete event system for HIV/AIDS treatment planning. IEEE International Conf. on Fuzzy Systems, vol. 1. 25-29 Budapest Hungary July (2004) 197-202