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Diagnoser with Hybrid Structure for Fault Diagnosis of a Class of Hybrid Dynamic Systems

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In this paper, we propose a new model-based approach for the fault diagnosis of hybrid dynamic systems (HDS), in particular discretely controlled continuous system (DCCS). The goal is to construct a diagnosis module (called diagnoser) able to diagnose parametric and discrete faults. Parametric faults are characterized by abnormal changes in some system parameters whereas discrete faults are attributed to undesired changes in the system configuration. This approach is based on a diagnoser with hybrid structure composed of three parts: discrete diagnoser, continuous diagnoser and coordinator. The discrete diagnoser is modelled as a discrete time hybrid automata model. It is used to detect and to isolate the discrete faults. The continuous diagnoser is based on a set of residuals comparing the measured and estimated values of each continuous variable in order to diagnose the parametric faults. The coordinator combines the discrete and continuous decisions of the two diagnoser sin order to diagnose faults requiring the interaction between both diagnosers.

1. Introduction

For industrial systems, fault diagnosis is crucial to achieve safe and reliable operations in spite of system faults. Most of real systems are hybrid dynamic systems (HDS) (Zaytoon,2001) in which the discrete and continuous dynamics cohabit. Thus, the diagnosis of these systems must deal with the evolution and the interaction of both continuous and discrete dynamics. The goal is to construct a diagnosis module (called diagnoser) able to diagnose parametric and discrete faults. Parametric faults affect the system continuous dynamics and are characterized by abnormal changes in some system parameters, whereas discrete faults affect the system discrete dynamics and are attributed to undesired changes in the system configuration.

Many approaches have been proposed in the literature to diagnose HDS. These approaches differ according to three criteria: the applied abstraction level, the used modeling tool (hybrid automata (Alur et al.,1993), hybrid Petri nets (Zhao et al., 2005), hybrid bond graph (Yu et al.,2012), ...) or the type of a priori knowledge about the process behavior (model-based (Derbel et al., 2009) or based on input/output of the system (Fourlas et al., 2003). They are generally divided into two main categories. The first category develops the continuous approaches, such as residual generation (Cocquempot et al., 2004) and causal graphs (Daigle et al.,2010), by integrating the discrete dynamics of the system in order to increase the diagnosis capacity (called diagnosability) of parametric faults (McIlraith et al., 2000) or to diagnose the discrete faults (Daigle et al.,2010).The second category develops the discrete approaches by integrating the continuous dynamics in order to enhance the diagnosability of discrete faults or to diagnose the parametric faults (Fourlas, 2009).Some approaches, as the ones in (Derbel et al., 2009) and the references therein, of this category capture the continuous dynamics by taking into account the time beyond events ordering. Thus, in this case, only some parametric faults violating temporal constraints or specifications between events occurrences can be diagnosed. Other approaches, as the ones in (Bhowal et al., 2007) and the references therein, take into account the continuous dynamics in order to improve only the diagnosability of discrete faults.

However, few approaches (Zhao et al., 2005) have been proposed for the diagnosis of both parametric and discrete faults in HDS. The diagnosis using these approaches may not become feasible when the

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number of discrete modes is very large. In addition, they are not efficient in the case of multiple fault modes. Finally, they do not scale well in the case of large systems.
In this paper, an approach for the diagnosis of both discrete and parametric faults in HDS is proposed. This approach exploits the system continuous and discrete dynamics as well as the interactions between them in order to enhance the diagnosability of discrete and parametric faults. In addition, this approach takes benefits of the modularity of the system in order to overcome the diagnosis complexity in the case of large scale systems. This approach is based on a diagnoser with hybrid structure (Figure 1). It consists of three parts: the discrete diagnoser, the continuous diagnoser and the coordinator. The discrete diagnoser is built using a discrete time hybrid automata model. Its goal is to detect and to isolate the discrete faults. The discrete diagnoser exploits the information extracted from the system continuous dynamics to get rid of diagnosis ambiguity due to the system behavior abstraction. The continuous diagnoser generates residuals comparing the measured and estimated values of each continuous variable in order to diagnose the parametric faults in each discrete mode. The information about the discrete mode is provided to the continuous diagnoser thanks to the information extracted from the discrete dynamics. Finally, the coordinator uses the decisions issued from the discrete and continuous diagnosers in order to diagnose faults requiring the interaction between both diagnosers.
The paper is organized as follows. Section 2 introduces the notations and definitions related to the proposed approach. Section 3 presents the different parts of the diagnoser with hybrid structure. A conclusion with future work direction ends the paper in section 4.

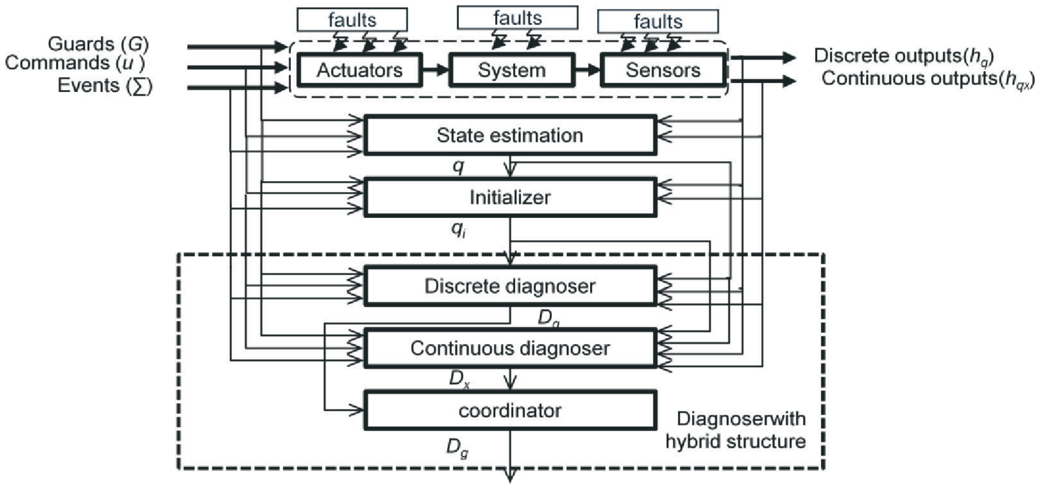

Figure1:Scheme showing the different parts of the diagnoser with hybrid structure

2. Definitions and notations

The discretely controlled continuous systemis modeled by adiscrete time hybrid automata:

$$A = (Q, X, flux, Init, Dom, \delta, G, R) \qquad (1)$$

Where,
$Q = \{q_i / i \in \{1, \dots, k\}\}$: is a finite set of discrete states of the system. The output of state q_i is characterized by d Boolean variables composing the discrete output vector $h_q = \{v_{1q}, \dots, v_{pq}, \dots, v_{dq}\}$;
$X = \{x_1, \dots, x_n\}$: is a finite set of continuous variables. The continuous state of the system is characterized at any time by the function $h_{qx}: \tau \times Q \to R^n$, where $h_{qx} = \{v_{1x}, \dots, v_{ix}, \dots, v_{nx}\}$ defines the continuous output at time t and in the discrete state q, where $x_i(t) = v_{ix}$;
The pair (q, X) represents the global state of the system;
$\Sigma = \Sigma_o \cup \Sigma_u$: is a set of finite events. It includes observable Σ_o and unobservable Σ_u discrete events.
$flux: Q \times X \to R^n$: is a function characterizing the temporal evolution $\dot{X}$ of continuous variables X in each discrete state q;
$Init \subset Q \times X$: is a set of initial conditions;
Dom: is the range of values that can take continuous variables in a discrete state;

We define a set of enablement conditions for the set of continuous variables in each state. Each condition g_{iqx} is represented by a linear inequality of the form $x\rho k_x$, where $x \in X$, $\rho \in \{\leq, \geq, =, <, >, \neq\}$ and $k_x \in \mathbb{R}$. This set of conditions is called transition guard $G_{qx} = g_{iqx}/i \in \mathbb{N}$, associated to each state$q$. G is the set of conditions associated to all the states of A.
$\delta: Q \times \Sigma \times G \to Q$: is the state transition function. A transition $\delta(q, e, G_{qx}) = q^+$ corresponds to a changefrom state q to state q^+ after the occurrenceof event e and theenablement condition G_{qx};
This transition changes the Boolean variables values, the domain and/or the evolution of continuous variables. Transition can be crossed only if the corresponding guard is satisfied and the corresponding event has occurred.
To describe the effect of occurrence of event e, a displacement vector T_{eq} is defined as a Boolean vector $T_{eq} = \{\tau_{e1q}, \dots, \tau_{epq}, \dots, \tau_{enq}\} \in \{0,1\}^d$. If$\tau_{epq} = 1$, then the value of p^{th} state variable h_q will be set or reset when e occurs. While If $\tau_{epq} = 0$, the value of p^{th} state variable h_q will remain unchanged when e occurs. Consequently, we can write: $\forall q, q^+ \in Q, \forall e \in \Sigma, q^+ = \delta(q, e, g_{qx}) \Longrightarrow h_{q^+} = h_q \oplus T_{eq}$;
$R: G \times \Sigma \times Q \times X \to \mathbb{R}^n$: is the reset function which initializes the continuous state variables in the new state q^+. If a transition does not contain a reset function, the variables preserve their initial values in q^+;
Σ_f: denotes the set of failure events to be diagnosed. The set of failure events is dividing into m different failure types or modes $\{F_1, F_2, \dots F_m\}$.
The following assumptions must hold:

- The model allows to describe the normal and faulty behaviors of the system;
- The continuous variables have a linear first order dynamics ;
- The considered faults can affect the sensors, the actuators or the physical system.

3. Diagnoser with hybrid structure

The approach proposed in this paper is a component oriented approach. Therefore, the system is decomposed into a set of plant components and a controller. The goal of this decomposition is to overcome the problem of large systems diagnosis by exploiting their modularity. The global system model is obtained by building state and transition tables for each component as well as for the controller. The state table provides a detailed description of the normal and faulty discrete states and their influences on the evolution of continuous variables. The transition table defines the initial state, the final state and the guards for each transition. In the next, the parts forming the diagnoser with hybrid structure are detailed.

3.1 Discrete diagnoser

The discrete diagnoser diagnoses the discrete faults by generating a decision D_q.
Every state z of the diagnoser is of the form ([state], [labels]), where labelsindicate the system operating status (faulty, normal).
Let $\phi(z) = \cup_{q \in z} \phi(q)$ where $\phi(z)$ defines the set of labels of the discrete diagnoser state z.
Definition 1: (Normal state)
The state $z = ([q_1, q_2, \dots], \phi(z))$ is called normal, If $\phi(z) = \{N\}$.
Definition 2: (F_i −certain)
The state $z = ([q_1, q_2, \dots], \phi(z))$ is called F_i −certain, if $\phi(z) = \{F_i\}$.
Definition 3: (F_i −uncertain)
The state $z = ([q_1, q_2, \dots], \phi(z))$ is called F_i −uncertain, if it has different labels.
Definition 4: (indeterminate cycle)
An indeterminate cycle is a sequence of F_i −uncertain state in which the diagnoser is unable to decide with certainty within a finite time delay the occurrence of a fault in Σ_f. The cycle is called indeterminate if the following two conditions are satisfied:

- It is a $\mathrm{F_i}$ −uncertain cycle in the diagnoser;
- Its states form two cycles in the model: the states of the first cycle have the normal label N whilethe states of the second cycle have the fault label $\mathrm{F_i}$.

The diagnosability consists in determining if the system model is rich enough in information in order to allow the diagnoser to infer the occurrence of predefined faults within a finite time after their occurrence. In discrete event systems, a system is not diagnosable if there is at least one indeterminate cycle. Inspired by the work in (Bhowal et al., 2007), our aim is to take benefit of the continuous dynamics evolution in order to get rid of the existence of indeterminate cycles.
*Proof 1:*Each state of the hybrid system is characterized by a different evolution of continuous variables and each transition validates certain number of guards associated with these variables. Consequently, in

an indeterminate cycle, the evolution of continuous dynamics of these variables changes. This change will entail the violation (non-satisfaction) of some guards associated to certain states in this cycle. Thus, the system will get out of this indeterminate cycle within a finite time.

Inspired by the definition of the diagnosability in discrete events systems (Sampath,1995),an extended notion of diagnosability of discrete faults in HDS is defined as follows:

Definition 5: The system S is said to be diagnosable with respect to the set of faults Σ_f if the following holds:

$$\left(\exists n_j \in \mathbb{N}\right)\left[\forall s \in \psi_{\Sigma_f}\right](\forall t \in L(S)/s)\left[|t| \geq n_j \Rightarrow D\right] \tag{2}$$

Where the diagnosability condition D is:

$$\forall y \in P_L^{-1}[P_L(st)], final(y) \in \Sigma_f \tag{3}$$

Where

$L(S)/s = \{t \in \Sigma^* | st \in L(S)\}$: denotes the set of event sequences after the event sequence$s$, Σ^* is the set of event sequences generated from the events in $\Sigma \cup \Sigma_G$.Σ_G is the set of events denoting the satisfaction of the guards;

ψ_{Σ_f}: is the set of all event sequences of $L(S)$that end with a failure event in Σ_f;

$P_L^{-1}[P_L(st)]$: corresponds to all the event sequences which have a projectionP_L, i.e. an observable event sequence, similar to the one ofst;

$final(y)$: is the failure event at which the event sequence$y$ ends.

The above definition of diagnosability means that the system S, defined by $L(S)$, is diagnosable with respect of the set of faults Σ_f if and only if all the event sequences containing a fault of typeF_i, has a finite observable part different from those of all the other event sequences generated by the system.

The discrete diagnoser is built based on the global model of the system. The transitions table of this diagnoser contains only the observable events and the measurable continuous variables. A state z of the diagnoser includes the states having the same observable discrete output. The transition $\alpha = (z, z^+)$ of the diagnoser is validated if and only if at least one of the transitions linking one of the states of$z$ with one of the states of $z^+$is validated. A transition between two states is validated if and only if the events related to this transition occurred and its guards are satisfied.

3.2 Continuous diagnoser

The role of the continuous diagnoser is to detect parametric faults, to determine their amplitude and to follow their evolution. It is based on the use of a set of residuals. The continuous diagnoser calculates its decision throughout two steps (Figure 2). In the first step, the measured and estimatedbehaviors of the system are compared in order to generate residuals.In the perfect case, residuals are equal to zero when the system is running in normal operating conditions and are different from zero when a fault occurs.In the second step, the residuals are analyzed to determine: (a) whether a fault has occurred or not (detection), (b) the responsible component (localization) in the case of fault occurrence and (c) the amplitude of the fault (identification).

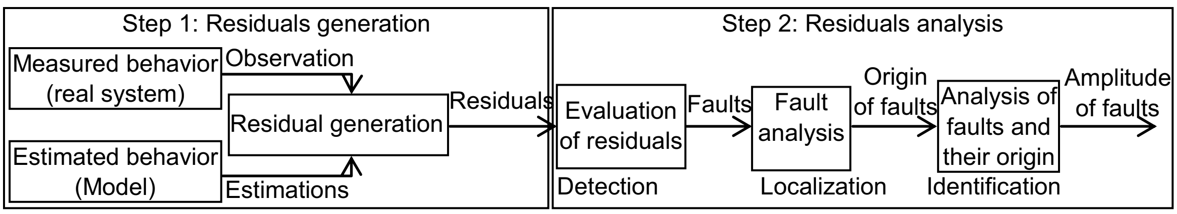

Figure2: Scheme of continuous diagnoser

The continuous dynamics of the system is described by the following linear differential equations:

$$\begin{cases} \dot{X} = AX + Bu \\ h_{qx} = CX + Du \end{cases} \tag{4}$$

u represents the command vector; A, B, C and D are constant matrices of appropriate dimensions. The equation (4) changes according to the discrete state of the system. The objective of the continuous diagnoser consists in estimating the values of the continuous variables by a vector $\hat{X}$ such as:

$$\begin{cases} \dot{\hat{X}} = A\hat{X} + Bu + L(h_{qx} - \hat{h}_{qx}) \\ \hat{h}_{qx} = C\hat{X} + Du \end{cases} \tag{5}$$

Where the matrix L, called gain matrix, must be chosen in such a way that all the eigenvalues of the matrix $(A - LC)$ have strictly negative real parts.
The continuous diagnoser generates several residuals, each one of them corresponds to a continuous variable. The residual corresponding to the continuous variable x_i is calculated as follows:

$$\begin{cases} \dot{\hat{x}}_i = A_i\hat{x}_i + B_iu + L_i(v_{ix} - \hat{v}_{ix}) \\ \hat{v}_{ix} = C_i\hat{x}_i + D_iu \end{cases} \tag{6}$$

The estimation error representing the residual related to x_i is:

$$r_i = v_{ix} - \hat{v}_{ix} \tag{7}$$

A signature is extracted from each residual by using two predefined thresholds r_{imax} and r_{imin}. The values of these two thresholds are determined as a trade-off between the rate of false alarms and the rate of non-detection. The symbol "0" means that the value of the residual is in the interval $[r_{imin}, r_{imax}]$, the symbol "$+$" means that the value of the residual is greater than r_{imax} and "$-$" means that the value of the residue is less than r_{imin}.
A symptom table, where each column represents a signature of fault $(+, -, 0)$ is build. It gathers the signatures of all the residuals according to each fault in Σ_f. Then, a decision tree is compiled based on the symptom table in order to determine the origin of the fault (localization). This fault localization is achieved by matching the path in the decision tree with the extracted signature using the real online observations. Each fault in the decision tree can be localized if and only if the columns of the table of symptoms are independent two by two.
After localizing the fault, a phase of identification is necessary to define the amplitude and the parameters of the fault, based principally on the eigenvalues of residuals. A decision of the continuous diagnoser D_x is generated containing [labels, fault parameters and amplitude].

3.3 Coordinator

The main objective of the coordinator is to detect all faults that require interaction between the continuous and discrete diagnosers. In other words, the coordinator is used to solve the potential ambiguity that can arise for the diagnosis of certain kinds of faults. Indeed, sometimes, a parametric fault (respectively discrete fault) can have a similar behaviour as a one of a discrete fault (respectively a parametric fault). In this case, both diagnosers declare parametric and discrete faults while in reality the final decision must be only the parametric fault (respectively the discrete fault). Therefore, the aim of the coordinator is to solve this ambiguity by declaring the right fault. The coordinator is constructed as follows. The condition table, where each row represents all the necessary signatures for detecting this fault, is established. Then, a decision tree is compiled based on the table conditions in order to generate the global decisionD_g. This decision treetakes into account theinteractions between the decisions of the continuous and discretediagnosers.

3.4 Initialization of the diagnoser with hybrid structure

The discrete (continuous) diagnoser and the system must be initialized at the same time, because the diagnosis decision of the discrete (continuous) diagnoser depends on the occurrence order of the events (the discrete mode and the trajectory of continuous variables in this mode). This initialization constraint is difficult to satisfy for the real systems. Therefore, the current discrete mode (state) of the system must be determined in order to initialize the discrete and continuous diagnosers at the right discrete mode or state. In order to achieve this task, the set of discrete states Q of the system is divided into two subsets $Q = Q_i \cup Q_{ni}$:

- The states $Q_i = \{q_{i1}, \dots\}$ that can be distinguished from the other system states by observing their output vector. The output vector of each one of these states is unique. Thus, the discrete and continuous diagnosers can be initialized at any of these states if the corresponding output vector is observed.
- The states $Q_{ni} = \{q_{ni1}, \dots\}$ that cannot be distinguished by observing their corresponding output vector because it is not unique. Thus, when observing one of the output vectors of these states, the discrete

and continuous diagnosers cannot be initialized because more than one state (discrete mode) has the same output vector.

We can initialize a diagnoser (continuous or discrete) in any state if this state belongs to Q_i. If it is not the case, the state belongs to Q_{ni}, the discrete and continuous diagnosers can be initialized if there is an integer $m \geq 0$ such as, after the occurrence of m state transitions, a state $q_i \in Q_i$ with a unique output vector can be observed. This concept is illustrated by the algorithm of (Figure 3) called initializer.

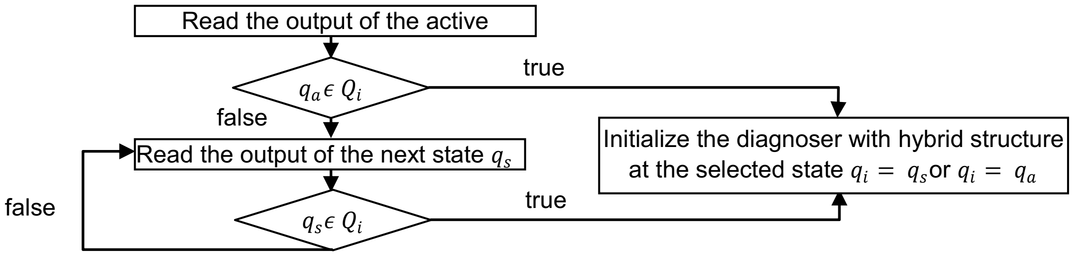

Figure3: Algorithm, called (initializer), illustrating the initialization of the diagnoser with hybrid structure

4. Conclusion

This paper proposes an approach for the parametric and discrete fault diagnosis of hybrid dynamic systems (HDS). The elaboration of this approach is motivated by the capacity of the hybrid models to represent intrinsically the interactions between the continuous and the discrete dynamics of a real system. The proposed approach is a diagnoser with hybrid structure which is divided into three parts: a discrete diagnoser, a continuous diagnoser and a coordinator. The discrete diagnoser allows detecting the occurrence of discrete faults, the continuous diagnoser allows diagnosing the parametric faults and the coordinator merges the decisions of both diagnosers in order to obtain a global decision. In future works, we aim at developing the proposed approach for the diagnosis of multiple faults in the case of large HDS.

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