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Towards Active Diagnosis of Hybrid Systems leveraging Multimodel Identification and a Markov Decision Process

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Abstract: Active diagnosis is defined as the association of fault detection and isolation algorithms with the execution of control plans that optimize fault research performance. This paper addresses active diagnosis of hybrid systems. It proposes to associate a diagnosis method based on multimodel identification and a framework for optimal conditional planning relying on a Markov decision process (MDP). The multimodel diagnosis algorithm identifies the most probable fault by measuring a distance between residual vectors generated from the test system and a set of reference fault models. Moreover a criterion called the correct diagnosis rate (CDR) is set up to evaluate the accuracy of the diagnosis results depending on the applied operation sequence. Conditional planning is formulated as a MDP, which is a model mixing a discrete structure and probabilistic variables. It is based on a reward function weighing diagnosis accuracy and the cost of actions and the optimal conditional plan is characterized thanks to the recursive Bellman function. An application to a diesel engine airpath model is presented so as to illustrate the diagnosis and planning methods in practice.

Keywords: Active diagnosis, hybrid systems, multimodel identification, Markov Decision Process.

1. INTRODUCTION

Car diagnosis is challenged by the unceasing evolution of car technologies. Technicians diagnosing car failures in repair workshops are helped in their task by decision support tools that need to be continuously enhanced. One opportunity to improve them is to combine fault detection and isolation (FDI) algorithms, which monitor the system behavior, with the application of relevant control laws, meant at boosting fault research performance. Such a mix of control and diagnosis is known as active diagnosis.

The first objective of our work is to set up an active diagnosis solution. It is a method integrating both a diagnosis algorithm and a conditional planning method that finds optimal sequences of actions based on the past observations. The method has been designed with the aim of being applicable to a family of hybrid systems, which consist of interactions between continuous and discrete dynamics, and to an industrial system: a diesel engine airpath. A third key objective is to integrate techniques belonging to two a priori distinct worlds of the literature, which are active diagnosis of continuous systems (CS) and test sequencing of discrete event systems (DES). The approach is thus built likewise (Bayoudh et al. 2009).

The literature of active diagnosis of CS is firstly composed of methods based on multimodel identification. On the one hand, diagnosis is formulated as determining from a set of models, each corresponding to a nominal or fault situation, the one that best fits the system behavior. On the other hand, planning for diagnosis is achieved, e.g. in (Blackmore & Williams 2006), through quadratic optimization on linearized systems and in (Šimandl & Punčochář 2009) through an generic control framework where an input generator interacts with a diagnosis module. The authors use a criterion balancing trajectory tracking and fault detection objectives and the optimal input is characterized thanks to the Bellman function. This framework includes the notion of Markov chain. In a similar spirit, (Gholami et al. 2011) bases its method on parameter estimation where optimal inputs are the ones that maximize the sensitivities of the parameters. Finally, (Eriksson et al. 2013) contributes to the active diagnosis literature, even if not explicitly stated. The goal is to analyze the effect of uncertainties and control inputs on the capacity to distinguish two fault models from each other thanks to a bank of residual. A distinguishability measure, based on the Kullback-Leibler norm, is set up so as to carry this analysis out.

In the literature oriented towards DES, (Bayoudh et al. 2009) presents a method of active diagnosis of hybrid systems cast in a DES framework. The system model, in the form of a hybrid automaton, is transformed into a purely discrete automaton and then into a diagnoser that integrates signature events obtained from residual signals with thresholds. A minimax search algorithm applied to the diagnoser finds conditional trajectories of modes that optimize fault discrimination. Besides, test selection for hybrid systems is addressed in (Pons et al. 2015). The paper details an algorithm using consistency based diagnosis principles. Then

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in (Chanthery et al. 2010) an application of active diagnosis of DES is developed based on an AO* heuristic search in a AND/OR graph derived from a diagnoser automaton. Besides, in (Pattipati & Alexandridis 1990) the authors formulate and solve a test sequencing problem based on a Markov Decision Process.

The method developed in this paper is, first of all, based on a simplifying hypothesis. The considered hybrid system Σ is considered to be remaining into a limited operation range called mode q, where discrete events do not occur and its behavior consists only of continuous dynamics. That is why the approach exploits a nonlinear model, typically used to represent continuous systems.

The first part of the method presents a diagnosis process based on multimodel identification, also called here multimodel diagnosis. The method explains how to generate residuals with multiple models and how to find the most probable fault by comparing the system residuals with the fault models ones, by means of a distance measure. Furthermore a new criterion, called the Correct Diagnosis Rate (CDR), is presented. Its function is to rate the confidence of a diagnosis depending on the uncertainty level and on the past sequence of actions. The multimodel diagnosis process is presented in section 2. The second part of the method outlines a framework for conditional planning for active diagnosis formulated as a Markov Decision Process (MDP). A new reward function based on the CDR and the cost of actions is proposed. Section 3 is dedicated to this MDP formulation. Finally, section 4 deals with the application of the method on an industrial model of a diesel engine airpath system. It illustrates its complexity and shows how to generate residuals, how to compute the CDR and finally how to solve a simple conditional planning scenario. Conclusions and perspectives are given in section 5.

2. MULTIMODEL DIAGNOSIS PROCESS

The first stage of the approach is dedicated to the design of a diagnosis algorithm along with a way to rate the relevance of its results. The process of multimodel diagnosis involves three steps which are the building of multiple fault models, the generation of residual sequences for the system and each fault model and finally the selection of the fault model whose residuals best match the system ones. Furthermore, a quantitative criterion called the Correct Diagnosis Rate (CDR) is introduced. Its role is to help guiding the process of active diagnosis by indicating how much confidence can be assigned to a diagnosis depending on the past sequence of actions.

2.1 System, control framework and multiple fault models

The system to diagnose is a hybrid system Σ, constrained into a limited operation mode q, where its dynamics are purely continuous. Its model is given, for each time $t_n \in \mathcal{T} = \{t_0, t_1, \dots t_{N_\mathcal{T}}\}$, by the following discrete-time stochastic state space representation:

$$\boldsymbol{x}_{n+1} = \boldsymbol{g}_n(\boldsymbol{x}_n, \boldsymbol{u}_n, \boldsymbol{f}, \boldsymbol{w}_n) \qquad (1)$$

$$\boldsymbol{y}_n = \boldsymbol{h}_n(\boldsymbol{x}_n, \boldsymbol{u}_n, \boldsymbol{f}, \boldsymbol{v}_n) \qquad (2)$$

where $\boldsymbol{g}_n$ and $\boldsymbol{h}_n$ are nonlinear vector functions. $\boldsymbol{x}_n \in \mathbb{R}^{Nx}$ is the continuous state of the system, $\boldsymbol{u}_n \in \mathbb{R}^{Nu}$ is the input, $\boldsymbol{y}_n \in \mathbb{R}^{Ny}$ is the output and $\boldsymbol{f} \in \mathbb{R}^{Nf}$ is the fault parameter. $\boldsymbol{w}_n \in \mathbb{R}^{Nw}$ and $\boldsymbol{v}_n \in \mathbb{R}^{Nv}$ are respectively the process and measurement noise variables. They are modeled by zero mean Gaussian probability density vector functions $p(\boldsymbol{w}_n)$ and $p(\boldsymbol{v}_n)$.

The system Σ is integrated in a generic closed-loop control architecture, shown in figure (1), where it is connected with a controller Γ. Hence the system behavior is more robust to uncertainties and in the specific case of automotive control, it helps preventing the engine to stall or to be overspeeding. The controller Γ is fed in a discrete-time approach by control actions $\boldsymbol{a} \in \Omega$, where Ω is the finite set of N_Ω control actions. A sequence of N_A consecutive actions $\boldsymbol{a}$ is denoted $\boldsymbol{A} = \{\boldsymbol{a}_0, \dots, \boldsymbol{a}_{N_A-1}\} \in \Omega^{N_A}$, while its associated time sequence is $\mathcal{T}_A$. $\boldsymbol{x}_0$ is the initial state of the system.

The essence of multimodel diagnosis is to anticipate the system fault behaviors by means of fault-dedicated models. The process of building fault models starts by defining a list of fault parameters. They represent the faults cases which may occur and that have not yet been discarded by other diagnosis means. The finite set of (N_F+1) fault parameters $\boldsymbol{f}_i \in \mathbb{R}^{N_f}$ is denoted $F = \{\boldsymbol{f}_0, \dots, \boldsymbol{f}_{N_F}\}$. $\boldsymbol{f}_0$ accounts for the nominal case. The single fault hypothesis holds, hence only one element of a parameter vector $\boldsymbol{f}_i \in F$ deviates from zero at a time. Moreover, various fault parameters can refer to the same fault, when different fault amplitudes are modeled. For example, biased measurement faults of 5% and 10% of a specific sensor can be modeled by two different fault parameters $\boldsymbol{f}_i$ and $\boldsymbol{f}_j \in F$.

A set of fault-dedicated models is finally obtained by replacing the variable $\boldsymbol{f}$ in the equations (1) and (2) by a fault parameter $\boldsymbol{f}_i \in F$, resulting in stochastic models denoted s_{f_i}. This set of multiple fault-dedicated models is denoted in a synthesized way, $S_{DIAG} = \{s_{f_i}\}_{f_i \in F}$. The set S_{DIAG} thus represents Σ in a whole range of anticipated fault situations.

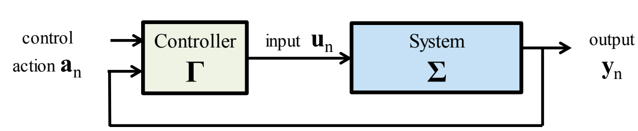

Fig. 1. The system Σ is associated to a generic controller Γ.

2.2 Residual generation

Now that each fault has its model, the motivation here is to generate the data on which to base the comparison between the system and the fault models. Most contributions in the active diagnosis literature do it by means of input-output data; see (Blackmore & Williams 2006) and (Šimandl & Punčochář 2009). However, a more generic alternative, widespread in the classical FDI literature, consists in using residuals instead. Residuals are signals resulting from a processing of the input-output behavior data of the system. Residuals are theoretically zero when there is no fault and