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A qualitative event-based approach to multiple fault diagnosis in continuous systems using structural model decomposition

Matthew J. Daigle[a,*,1], Anibal Bregon[b,2], Xenofon Koutsoukos[c], Gautam Biswas[c], Belarmino Pulido[b,2]

[a] NASA Ames Research Center, Moffett Field, CA 94035, USA
[b] Departamento de Informática, Universidad de Valladolid, Valladolid 47011, Spain
[c] Institute for Software Integrated Systems, Department of Electrical Engineering and Computer Science, Vanderbilt University, Nashville, TN 37235, USA

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ABSTRACT

Multiple fault diagnosis is a difficult problem for dynamic systems, and, as a result, most multiple fault diagnosis approaches are restricted to static systems, and most dynamic system diagnosis approaches make the single fault assumption. Within the framework of consistency-based diagnosis, the challenge is to generate conflicts from dynamic signals. For multiple faults, this becomes difficult due to the possibility of fault masking and different relative times of fault occurrence, resulting in many different ways that any given combination of faults can manifest in the observations. In order to address these challenges, we develop a novel multiple fault diagnosis framework for continuous dynamic systems. We construct a qualitative event-based framework, in which discrete qualitative symbols are generated from residual signals. Within this framework, we formulate an online diagnosis approach and establish definitions of multiple fault diagnosability. Residual generators are constructed based on structural model decomposition, which, as we demonstrate, has the effect of reducing the impact of fault masking by decoupling faults from residuals, thus improving diagnosability and fault isolation performance. Through simulation-based multiple fault diagnosis experiments, we demonstrate and validate the concepts developed here, using a multi-tank system as a case study.

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1. Introduction

Safety-critical systems require quick and robust fault diagnosis mechanisms to improve performance, safety, and reliability, and enable timely and rapid intervention in response to adverse conditions so that catastrophic situations can be avoided. However, complex systems can fail in many different ways, and the likelihood of multiple faults occurring increases in harsh operating environments. Diagnosis methodologies that do not take into account multiple faults may generate incorrect diagnoses or even fail to find a diagnosis when multiple faults occur.

Multiple fault diagnosis in static systems has been addressed previously (de Kleer and Williams, 1987; Struss and Dressler, 1989; Abreu and van Gemund, 2010), where the inherent complexity of the problem has been well demonstrated; the diagnosis space becomes exponential in the number of faults, and this complicates the diagnosis task. Furthermore, in dynamic systems, the problem is even more challenging, as the effects of multiple faults may mask one another, thus making it difficult to differentiate between multiple fault diagnoses (Dvorak and Kuipers, 1991; Nyberg and Krysander, 2003; Daigle et al., 2007a). Due to fault masking, multiple faults can produce a variety of different observations, and this adds uncertainty, which, in turn, reduces the discriminatory ability of the diagnosis algorithms. Moreover, the more faults considered, the more possible ways in which their effects can interleave, making it less likely that the fault diagnoses can be uniquely isolated given a set of observations.

Due to its complexity, multiple fault diagnosis of dynamic systems has not been sufficiently addressed in the literature. In Ng (1990), changes are modeled by a set of qualitative simulation states. Later, Subramanian and Mooney (1996) integrated the model-based diagnosis approach in de Kleer and Williams (1987) and the qualitative reasoning approach in Ng (1990), to multiple fault diagnosis for dynamic systems using behavioral modes with a

* Corresponding author.
E-mail addresses: matthew.j.daigle@nasa.gov (M.J. Daigle), anibal@infor.uva.es (A. Bregon), xenofon.koutsoukos@vanderbilt.edu (X. Koutsoukos), gautam.biswas@vanderbilt.edu (G. Biswas), belar@infor.uva.es (B. Pulido).

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priori probabilities. In a related approach, semi-quantitative simulation is used (Dvorak and Kuipers, 1991), changing the configuration of the model every time a fault appears. However, in these kinds of approaches, the qualitative modeling framework quantizes the state space and specifies qualitative relations between the quantized states, which can result in a large number of states, i.e., such approaches can suffer from the state explosion problem.

In control theory-based diagnosis approaches (known as fault detection and isolation, or FDI approaches), the proposal in Gertler (1998) is based on the analysis of residual structures. In Nyberg and Krysander (2003), the authors integrate residual-based and consistency-based approaches that can automatically handle multiple faults in dynamic systems. However, these approaches use only binary signatures (effect or no effect), and so it becomes very difficult to distinguish between different potential multiple faults.

In contrast, our previous work in multiple fault diagnosis for continuous systems (Daigle et al., 2007a; Daigle, 2008) is based on a qualitative fault isolation (QFI) framework (Mosterman and Biswas, 1999). It describes how multiple faults manifest in the system measurements and provides algorithms for fault isolation. By using qualitative information defined with respect to a nominal reference, the state explosion of qualitative simulation approaches is avoided. Unlike other FDI approaches, diagnostic information is enhanced using qualitative symbols, instead of binary effect/no effect information, and by including the sequence of observations.

The QFI approach was based on using residuals (the difference between observed and expected system behavior) computed from a global system model. Since faults affect all residuals that have a causal path from the fault to the residual, fault masking can have a significant, adverse impact on multiple fault diagnosability when the number of residuals affected by a fault is large. To avoid this problem, in Daigle et al. (2012), we explored the idea of using structural model decomposition to improve diagnosability, by deriving local submodels that decouple faults from residuals, so that each fault affects only a small set of residuals (Gertler, 1998; Roychoudhury et al., 2013). This decreases the possibility of masking, and, as such, leads to improvements in multiple fault diagnosability.

In this paper, we extend the previous work in event-based QFI of single faults (Daigle et al., 2009) to develop an online multiple fault diagnosis approach for dynamic systems that takes advantage of structural model decomposition. In this framework, diagnostic observations take the form of symbolic *traces* representing sequences of qualitative effects on the residuals. First, we develop a systematic approach for predicting the possible traces that can be produced by multiple faults, based on a specific composition of those produced by the constituent faults. Second, we develop an online fault isolation algorithm that maps observed traces to the set of minimal diagnoses that could have produced that trace. Third, we introduce definitions of diagnosability to characterize the potential fault isolation performance for different residual sets, and show how structural model decomposition can significantly improve diagnosability in the multiple-fault case. Fourth, using a multi-tank system as a case study, and over a comprehensive set of simulation-based experiments, we provide offline diagnosability results and online multiple fault isolation results to (i) demonstrate and validate the overall approach, (ii) illustrate the improvement in performance obtained through the use of structural model decomposition, and (iii) show the performance improvement over approaches that use binary fault signatures without temporal information. The multi-tank system is also used as a running example throughout the paper.

The paper is organized as follows. Section 2 presents our modeling background and formulates the multiple fault diagnosis problem. Section 3 overviews the structural model decomposition approach, and develops the qualitative fault isolation methodology for multiple faults, which predicts the possible traces that can be produced by a set of faults. Section 4 presents the online multiple fault isolation approach, which determines the set of faults that can produce an observed trace. Section 5 formalizes our definitions of distinguishability and diagnosability in order to characterize the fault isolation performance of a system using our approach. Section 6 presents the results for the case study. Section 7 describes related work in multiple fault diagnosis. Section 8 concludes the paper.

2. Problem formulation

In this work, we consider the problem of multiple fault diagnosis in continuous systems. We first overview our system modeling approach, followed by a definition of the multiple fault diagnosis problem.

2.1. System modeling

In our framework, a model is defined as a set of variables and a set of constraints among the variables (Roychoudhury et al., 2013):

Definition 1 (*Constraint*). A constraint c is a tuple (ε_c, V_c), where ε_c is an equation involving variables V_c.

Definition 2 (*Model*). A *model* $\mathcal{M}$ is a tuple $\mathcal{M} = (V, \mathcal{C})$, where V is a set of variables, and $\mathcal{C}$ is a set of constraints among variables in V. V consists of five disjoint sets, namely, the set of state variables, X; the set of parameters, Θ; the set of inputs, U; the set of outputs, Y; and the set of auxiliary variables, A.

The set of output variables, Y, corresponds to the (measured) sensor signals. Parameters, Θ, include explicit model parameters that are used in the model constraints. Auxiliary variables, A, are additional variables that are algebraically related to the state, parameter, and input variables, and are used to reduce the structural complexity of the equations. The set of input or exogenous variables, U, is assumed to be known.

In this paper, we use a multi-tank system as a case study. The system consists of n tanks connected serially, as shown in Fig. 1.

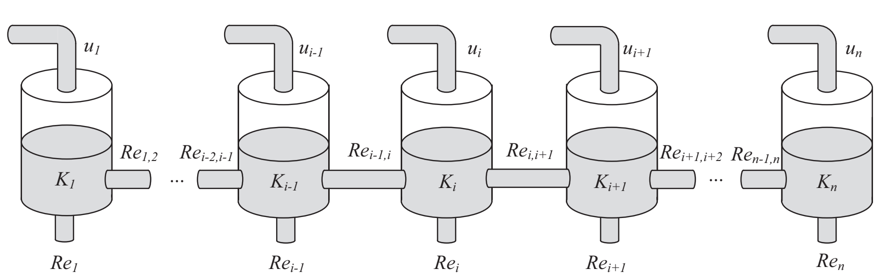

Fig. 1. Tank system schematic.