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The effectivity analysis of adding sensors for improving model based fault isolability properties

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ABSTRACT

In order to improve the fault isolability properties of a diagnosis system, a usual way is to add sensors for measuring extra state variables. Unlike previous literatures that usually focus on adding new sensors to fulfill diagnosis specifications, this paper aims to analyze the influences on the isolability properties when more variables are measured.

Using structural model decomposition, the equations and variables of a system model are separated into different categories. Then, the association relations between the fault equations can be extracted, which imply the fault isolability. According to the partitions of variables, the selection space of adding sensors is significantly reduced. It is useful to optimize sensor placement and enhance fault isolability. Moreover, our approach need not build a fault signature matrix for fault diagnosis. The efficient algorithms based on this approach are proposed and the simulation of a four-tank system indicates the validity of the method.

1. Introduction

In model-based diagnosis, fault diagnosis is performed based on checking the consistencies of system redundancies, i.e. comparing the system model and on-line system information. Generally, obtaining system information is strongly dependent on available sensor measurements, and in turn for a diagnosis system the sensor placement greatly affects fault detectability (the ability of detecting a fault occurrence) and fault isolability (the ability of distinguishing between two possible fault occurrences). In order to enhance the fault isolability properties of a diagnosis system, a usual way is to add sensors for measuring extra state variables until the requirements are satisfied [1]. Additionally, it is often considered that the more sensors are installed in a system, the better fault isolability properties can be expected. However, the fault isolability properties cannot always be improved by adding sensors. On the other hand, that may raise the instrumentation cost and system complexity. Therefore, for handling the problem of optimal sensor placement, it is necessary to analyze the effectivity of adding sensors for improving the fault isolability properties.

In the last decades, quite a lot of works utilize structural analysis to solve the sensor placement problem [2–5]. The structural analysis approach, that is an important branch of model-based diagnosis, uses the structural model of a diagnosis system to identify the structural properties for fault diagnosis. Here, a structural model is a graph representation of a system model, since only the relation between variables and equations is taken into consideration [6]. In other words, in a structural model the explicit analytical form of the model equations are not considered. Since no numerical problems need to be solved, this kind of models can be handled by efficient graph-based tools. So, structural analysis generally has better computational efficiency than analytical method. In a word, structural analysis is suitable to deal with large scale and complex systems [7–10], and can be used in the early design stage of a diagnosis system [11].

Usually, some new sensors are added to measure more state variables in a system for fulfilling the diagnosis specifications. In [3], in order to determine which sensors should be added to obtain maximum fault detectability and isolability, the authors make use of computing minimal hitting sets to look for the solution. But, for a large scale and complex system, this is not an easy issue. Moreover, from the viewpoint of analyzing fault diagnosability, the paper does not provide the influences to the fault isolability properties of the original system when different state variables are measured. In [4], the author presents the equivalent effect between the diagnosability properties achieved by installing a set of sensors to a system at a time and the properties achieved by installing individual sensor one by one. However, the paper also does not present

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whether the diagnosability properties can be enhanced when different state variables are measured by new sensors. In [12], for reducing the computational complexity, the authors combine clustering techniques with a branch and bound search strategy based on a structural model to solve the sensor placement problem. But the paper does not concern the effectivity analysis of adding sensors for improving fault isolability properties. In a word, all these literatures have in common that they all mainly focus on how to add sensors to improve the fault diagnosability. However, in the field of model-based diagnosis, few researches estimate the influences on the isolability properties of a diagnosis system when any state variable is measured by an additional sensor.

For solving the problem of sensor placement, this paper analyzes the effectivity of adding sensors for enhancing the fault isolability properties by using structural analysis. In our approach, through structural model decomposition, all the model equations and the state variables of a diagnosis system are classified. In other words, based on the structural properties of the system model, all the state variables are partitioned into two types of variable sets. For the first type of variable sets, adding sensors to measure those variables cannot change the isolability properties. For the second type of variable sets, which are some exclusive sets of variables, only measuring some variables in one of the sets may let two corresponding indistinguishable faults be isolable from each other. Furthermore, the condition of improving the fault isolability properties is presented. The above conclusions significantly reduce the selection space of additional sensors. That are useful to optimize sensor placement and enhance the diagnosability properties of a given diagnosis system. On the other hand, in the aspect of computation cost, our method is based on structural models. This means that non-linear differential systems can be efficiently handled. Moreover, it need not determine all of the Minimal Structurally Overdetermined (MSO) sets of a system model [13] for identifying the fault isolability. Then, the computation burden of finding all MSO sets is avoided. Here, an MSO set is a subsystem model with one degree of redundancy, i.e. the set of equations has one more equation than the number of unknowns.

Recently, the approach of fault signature matrix (FSM), a classical diagnosis approach, has been extensively applied in the field of model based diagnosis [14]. In this paper, the FSM approach is adopted to check the results computed by the new approach. The FSM is a boolean matrix, where the rows correspond to the set of residuals and the columns the set of faults. An *ij*-element of the matrix contains the pattern 1 means that fault *j* can be detected by the *i*th residual, 0 otherwise. The *j*th column constructs a binary word that is called the *signature* of the fault *j*. If two signatures are identical, the corresponding faults are said to be no distinguishable. On the other hand, the residuals in a FSM are usually derived from all MSO sets of a system model, but the number of MSO sets grows exponentially with the redundancy degree [15]. In this paper, for the sake of simplification, it is assumed that a single fault *f* can only affect one equation (known as fault equation, denoted by e_f), then the fault isolability relations can be transformed into the incidence relations between fault equations. A sensor *s* only measures one single unknown variable, and the sensor measuring is valid with no sensor fault.

The rest of this paper is organized as follows. Following the introduction session, Section 2 presents the background of structural analysis. Section 3 proposes the fault isolability properties of an overdetermined system, and shows its influences when extra variables are measured, which are used as a theoretical basis for effectively improving the fault isolability properties. In Section 4 the corresponding new algorithms of this method are provided and the validity of the approach is verified by the results of a benchmark four-tank system in Section 5. Finally, this paper is summed up in a conclusion in Section 6.

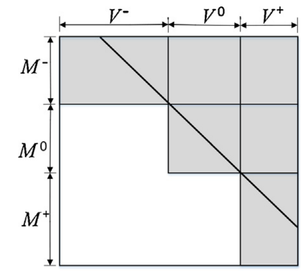

Fig. 1. Dulmage-Mendelsohn decomposition of a model *M*.

2. Background of structural analysis

2.1. Bipartite graph and matching

In the field of structural analysis, a structural model is usually represented by a bipartite graph (or equivalently its incidence matrix) with equations and unknown variables as node sets [11]. A bipartite graph $G(E, V, A)$, where E is a set of model equations, V a set of unknown variables and A a set of edges. An edge $(e_i, v_j) \in A$, as long as the variable v_j is included in equation e_i, for $e_i \in E$ and $v_j \in V$. The corresponding incidence matrix M of G is a boolean matrix, where the rows correspond to the set E of equations and the columns the set V of variables. $M(i, j) = 1$ if $(e_i, v_j) \in A$, 0 otherwise. Note that the known variables of a system model are not considered since they will not be used in this paper.

In addition, a key role, in the context of structural analysis, is played by the notion of matching in a bipartite graph. It is used to identify overdetermined subsystems that imply the diagnosability properties of a diagnosis system. A matching is a subset Γ of edges such that any two edges in Γ have no common node. A maximum matching is a matching with the maximal number of edges in G.

2.2. Dulmage-Mendelsohn decomposition

The Dulmage-Mendelsohn (DM) decomposition is a powerful theoretical tool for structural analysis [16]. It only uses the row and column permutations on an incidence matrix to derive an upper triangular form. This decomposition is shown in Fig. 1, where the gray-shaded parts correspond to ones and zeros, but the white parts only correspond to zeros. The bold line in the matrix indicates a maximum matching. It represents an oriented calculation path that can be performed sequentially, in other words, from a maximal matching the variables can be calculated by the equations.

An important property of the DM decomposition is that it splits the model M into three partitions, namely, the overdetermined part M^+ with more equations than unknown variables, i.e. $|M^+| > |V^+|$; the justdetermined part M°, $|M^\circ| = |V^\circ|$; and the underdetermined part M^-, $|M^-| < |V^-|$, Where $|\bullet|$ denotes the cardinality of the set. It should be noted that only the overdetermined part includes redundancy, and only this part is useful for fault diagnosis [11] [13].

For any finite-dimensional bipartite graph, the three main partitions of the DM decomposition are unique, which is irrelevant to the choice of a maximum matching [17]. In this work, the decomposition can be implemented efficiently using the *dmperm* command of MATLAB®.

2.3. Basic concepts on model-based diagnosis

In this part, some basic concepts are provided to describe fault isolability properties.