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Towards Identifying Useful Sorts of Knowledge and Strategies for Diagnosing Faults: A Framework for Hypothesis Generation

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1 Introduction

As can be found in [1], model-based diagnosis (MBD) can be considered a method of diagnosis that uses the notions of structure and behavior of the device being diagnosed to detect faults from an observed symptom. Although stated in slightly different terms in [1], in general, MBD can be divided into three subtasks: ***Hypothesis Generation*** at which possible fault hypotheses are generated, given a symptom;***Hypothesis Testing*** where the fault hypotheses are tested if each of them can account for the symptom or not, and then those which can not account for the symptom will be discarded; and ***Hypothesis Classification*** where the fault hypotheses that passed the test will be classified into an expected order. In each subtask, the problems are: What sorts of knowledge can be used ? What kinds of strategies can be applied ?

In this paper, we focus on the subtask hypothesis generation. We propose an approach to the subtask, providing a framework at which crucial sorts of knowledge and strategies for diagnosing faults, structural faults as well as behavioral faults, are covered.

2 Hypothesis Generation

Our framework for hypothesis generation is shown in Fig. 1. To generate fault hypotheses from a given symptom, the framework considers three important information sources for diagnosis: the *domain model*, *additional domain knowledge*, and *diagnostic strategy*. The domain model can be regarded as a class of knowledge that is useful for modeling the system being diagnosed. Different from this knowledge class, the additional domain knowledge is a class of knowledge that is helpful in diagnosing faults, but the knowledge itself can not be derived from the system directly. The diagnostic strategy can be considered to be a set of strategies for diagnosis. In the rest of this section, we explain the knowledge sorts, strategies, and algorithm in rather detail.

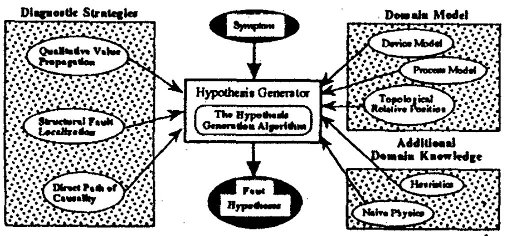

Figure 1: Hypothesis Generation

2.1 Domain Model

For the task of hypothesis generation, the domain model includes the device model, process model, topological relative position.

```
compressor
    purpose: state 1:            outpress(gas) = HIGH
    processes:                   compression(gas,compressor)
    terminal:
        input  1: connection:    conduit4
                  parameters:    inflow(gas), inpress(gas), intemp(gas)
        output 1: connection:    conduit1
                  parameters:    outflow(gas), outpress(gas), outtemp(gas)
    constraints: state 1:        [inpress(gas) + [addpress] = [outpress(gas)]
                                 [addpress] = POS_CONST
                                 [inpress(gas)] = M+[intemp(gas)]
                                 [outpress(gas)] = M+[outtemp(gas)]
                                 [inflow(gas)] = M+[outflow(gas)]
```

Figure 2: Device Model 1

In principle, the device model represents the structure and behavior of a component in the device. However, for the purpose of diagnosis, another information such as the purpose of the component being modeled is usually added into the model. Our device model is represented in the form of a frame that includes a description of the *purpose* of the component, a set of *processes* that are active when the component works, a set of components that are *connected* to the component, a list of *parameters* that are used for interaction between the component and the other components connected to the component, and a set of *constraints* describing the behavior of the component in terms of qualitative derivative equations.

Therefore, by means of the device model we can model a compressor in a refrigeration plant as shown by Device Model 1 in Fig. 2.

Besides being able to be represented in terms of structure and behavior, a system can be described in terms of the processes being active in the system. In the process model, we model processes that are active in the system under consideration. As in [2], we describe a process in the form of a frame that is specified by the following four slots: *individuals*, a set of objects that participate in the process; *initiating conditions*, a set of conditions which must hold for the process to start; *sustaining conditions*, a set of conditions which must hold for the process to continue; and *effects*, a set of value parameters which are influenced by the process. Process Model 1 in Fig. 3 shows a process model for liquid compression in the compressor.

```
compression(liquid,compressor)
    individuals:             liquid, compressor
    initiating conditions:   exist(liquid, compressor)
    sustaining conditions:   addpress(compressor) = +
    effects:                 press(liquid) = +
```

Figure 3: Process Model 1

Unlike the two sorts of knowledge above, the topological relative position presents the information, describing the relations among components in the device in terms of space. This kind of information is useful for controlling combinatorial explosions in generating fault hypotheses, particularly structural faults. Topological Relative Position 1 in Fig. 4 shows a very primitive topological relative position for an outdoor unit of an air-conditioner.

```
outdoor-unit
    inside:  compressor
             propeller_fan
             conduit1
             conduit2
             conduit4
```

Figure 4: Topological Relative Position 1

2.2 Additional Domain Knowledge

In fact, the first task the hypothesis generator has to do is to interpret the given symptom. Most of approaches to MBD take an assumption that symptoms can be interpreted directly in terms of parameter values. However, in fact, not all observed symptoms can be interpreted in terms of parameter values. Therefore, in order to be able to interpret such a symptom, at least a certain extent of diagnostic knowledge on the domain is needed. That is to say, we need heuristics to cope with it. For instance, the following states that knocking at the compressor can be caused by liquid compression at the compressor:

Heuristics 1:
knocking(compressor) ⇐ *compression(liquid, compressor)*

Moreover, from the style of reasoning, diagnosis can also be considered, although not absolutely, postdiction. It means that the task is to deduce how the state shown by a given symptom might have happened. To do the task often requires naive physics, which is not available in the structure and behavior of the device under consideration. We use *taxonomies* as in [3], to formalize naive physics. Naive Physics 1 in Fig. 5 shows the "exist" history of liquid. The element in the left-hand side (lhs) indicates the concept of "exist" of matter in the liquid state, while those in the right-hand side (rhs) shows phenomena causing it. Processes similar to those in the process model are used to charaterize those phenomena in more detail.

Don't confuse the naive physics with the heuristics. The former is our common sense about the everyday physical world, while the latter is a particular diagnostic knowledge of a domain that is obtained by experience.

liquid: *exist(liquid,X)* ⇐ *flowing(liquid,Src,X)* V
melting(solid,X) V
condensation(gas,X)

Figure 5: Naive Physics 1

2.3 Diagnostic Strategy

Two common strategies known widely in the current MBD are the qualitative value propagation and the direct path of causality. The former states that to generate fault hypotheses, particularly behavioral fault hypotheses, in a device, given an observed symptom, it is important to interpret the observed symptom which usually can be interpreted in the level of a parameter value as a qualitative value rather than as a quantitative (numerical) one, then propagate the qualitative value through the whole device model of the device. The latter is then applied in order to reduce the space of searching during the process of diagnosing. Thus, it is enough to propagate an observed symptom in the opposite direction of the information flow in the device.

Applying only the two strategies described above, however, we can not detect the so-called structural fault. This is because the structural modifications of the device also cause changes to the path of causality in the device. As a way to solve the problem, we use mainly the naive physics, the topological relative position, and the device model to detect the fault from the effect of the fault. The detection can be explained as follows. First, we use the naive physics to deduce how the state shown by the symptom might have come about; if necessary, we use the heuristics. Next, we use information on the corresponding processes to detect possible faults. Finally, using the topological relative position of the device we screen the possible faults then localize possible structural faults with the device model of the device.

2.4 The Hypothesis Generation Algorithm

The mechanism of generating fault hypotheses that exploits the sorts of knowledge and the strategies described in the previous subsections is shown schematically in Fig. 6.

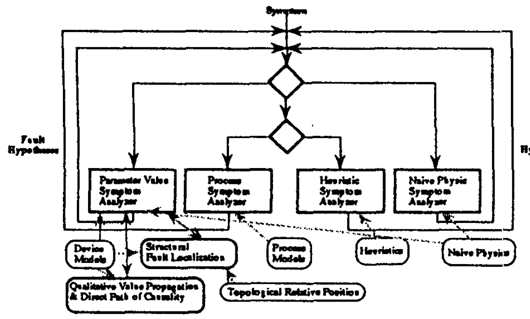

Figure 6: The Hypothesis Generation Mechanism

In order to be able to use the sorts of knowledge directly in generating fault hypotheses, we classify symptoms into four types, namely, parameter value symptoms, process symptoms, heuristic symptoms, and naive physics symptoms. The mechanism consists of four different symptom analyzers, each of which corresponds to each of analyzers for the four types of symptoms. Given a symptom, using appropritely the five sorts of knowledge and the three strategies if needed, the mechanism generates fault hypotheses which can be derived directly from the symptom and then takes the fault hypotheses as new symptoms to generate further fault hypotheses. This is done repeatedly until all possible fault hypotheses are generated or a certain number of fault hypotheses are achieved. The hypothesis generator (HG) is built based on the mechanism. The detailed algorithm can be found in [4].

3 Example

Here we show an example of how the above framework diagnoses faults. Consider a fault case in an air-conditioner as shown in Fig. 7. Assume that the valve between the expansion valve and conduit 2 drips and the drip flows into the compressor. This causes liquid compression at the compressor, which finally results in knocking at the compressor (See the broken lines in Fig. 7).

The sequence of the diagnosis of the structural fault can be explained as follows. (Follow the diagnosis sequence shown in Fig. 8, while reading the following explanation.)

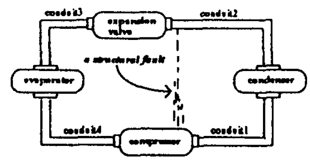

Figure 7: An Elementary Refrigeration Plant with A Structural Fault

First, the HG finds that the symptom is at the level of heuristics. It coincides with the element in the lhs of *Heuristics 1*. The HG then activates the rhs of the corresponding rule, which leads to consider that Process Model 1 is active.

The HG then sets the process as a new symptom and proceeds with its postdiction, scanning the slots of the process. In the initiating conditions, It finds *exist(liquid,compressor)* and then makes it to be a new symptom. This will move the focus of attention of the HG to the Naive Physics 1, which leads to consider that process *flowing(liquid,Src,compressor)* was active (for simplicity, the other processes are ignored). The HG then again sets the process to be a new symptom.

The HG then begins scanning the slots of the process and finds that what is possible to be the Src of the process is a ***contained-liquid***. Next, by means of Topological Relative Position 1: outdoor-unit and the device model of conduit2, the HG knows that conduit2 is a contained-liquid and is possible to be the Src since it is in the same room as the compressor. This leads the HG to deduce that there is ***a new connection as a liquid-flow-path between conduit 2 and the compressor***, which leads us to think that perhaps ***liquid leaking out of the valve between the expansion valve and conduit 2 flows into the compressor***.

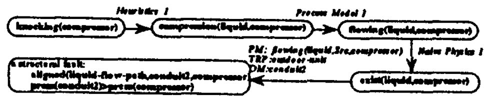

Figure 8: A Diagnosis Sequence

4 Conclusion and Future Work

In this paper we have shown the importance of the device model, the process model, and the topological relative position for modeling a device, and the use of them in diagnosing faults, and pointed out that the heuristics and naive physics have also to be considered, particularly, in diagnosing structural faults. We also have indicated, although not explicitly, that the use of multiple diagnostic strategies in diagnosing faults enhances the capability of the hypothesis generator.

Besides implementing the current framework, we are also currently doing research on providing frameworks for the other two subtasks of diagnosis, i.e., ***Hypothesis Testing*** and ***Hypothesis Classification***, which finally will be combined with the current framework to provide a robust framework for model-based diagnostic systems.

References

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