Event-Based Diagnosis for Evolutive Systems

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Abstract

This paper presents a new view of model-based diagnosis for evolutive systems. The possible behaviors of the evolutive system are captured by a set of events that can affect its current state. Diagnosing amounts to determining the history of the system, in terms of a sequence of events representing what may have happened to the system between two or more successive observations. This approach is particularly useful when explaining successive observations requires taking the history of the system into account. It allows precedence constraints between faults, as well as intermittent and non-intermittent faults to be modeled. It provides a unified representation and treatment of the various types of evolutions of the system's state: evolutions due to internal faults, to exogeneous events, as well as to test/repair actions.

1 MOTIVATION

Model-based diagnosis, which consists in identifying malfunctioning components in a device by confronting observations to predictions from a model of the device's behavior, has received a lot of attention in this last decade. For long, model-based diagnosis has been studied in the context of static systems, i.e., systems that are assumed to be invariant throughout the diagnosis process [13, 3]. In this context, little attention has been paid to the history (past, evolution) of the device. A first step in this direction has been the use of non-intermittency assumptions [12] to improve discrimination between diagnoses.

More recently, it has been recognized that most real systems are changing along time, and recent research work claims the need for representing time in model-based diagnosis [8, 6, 1]. In that respect, the use of qualitative models based on QSIM [9], as in [5, 11, 10], seems to be well-adapted to the monitoring of dynamic processes, as long as qualitative laws can easily be provided. On the other hand, [6] proposes to extend the consistency-based approach in a very general way by allowing an explicit use of time points. A state of a system accounts for different time points and a temporal diagnosis is defined as a state that is consistent with the observations. This purely logical approach is powerful in that it allows the description of the statics and dynamics of the system within the same formalism, but is unrealistic from a computational point of view. [1] proposes to decompose a time-varying system into a sequence of static systems, each of which can be handled using traditional techniques. The dynamic part is captured by a set of component-oriented transition graphs. A temporal diagnosis is then a sequence of static diagnoses obeying the transition constraints between states. This decomposition is interesting to gain efficiency and makes the reuse of the machinery developed for static domains possible. However, it is based on the assumption that the evolution of the complete system can be represented by the independent evolution of its components, which is often too restrictive.

We propose to define temporal diagnoses as sequences of events (hence the name "event-based" diagnoses) rather than as states or sequences of states as it is usually done. A diagnosis problem consists then in answering the question "What happened to the device between two (or more) successive observations?" rather than the classical question: "In which (abnormal) state is the device?". The events constituting a diagnosis correspond to components changing from a mode to another, to external events which have affected the device's behavior, or to events relative to the own dynamics of the device.

The main advantages of this new view of diagnosis are the following:

- Our approach is quite adapted to the description of dynamic systems as soon as their behavior can be represented as a discrete event system. This latter assumption can reasonably be made, and underlies the work in qualitative modeling. This ability is particularly useful for tasks that, such as monitoring evolutive systems, require taking the history of the system into account in order to explain successive observations.

  Our framework is suitable to static systems as well. The system is then supposed to have changed from a normal state (in which all components are correct) to the current state.

- The event-based approach provides a unified representation of the various evolution types of the system: internal changes, exogeneous events as well as test and repair actions.
- Temporal constraints between events, such as precedence constraints between faults, can easily be expressed via the preconditions of the events (i.e., the conditions under which the event may occur). Non-intermittency of faults can also be expressed by the absence of an event allowing a component to turn from a faulty to a normal state.
- In our framework, the diagnosis process amounts to finding a "preferred" scenario followed by the system according to observations made at successive time instants. Preferences between diagnoses can be naturally expressed as preferences between sequences of events as will be seen in Section 4.

The paper is a short version of [2]; it is organized as follows. Section 2 introduces the notion of a system in our framework. Section 3 defines an event-based diagnosis problem and characterizes its solutions. Section 4 deals with preferred and explanatory diagnoses. Section 5 compares our approach to related work, and discusses future work.

2 SYSTEM

We begin with defining the notion of a system in our framework. We consider two types of information in order to model the behavior of a system.

Information referring to the system's statics. Relevant features of the states of a system are captured by a vector of state variables $X = (x_1, \dots x_n)$, each variable x_i ranging over a domain D_i. A state of the system is then just a value assignment to each of the state variables, i.e., an element of the state space $D = \Pi_{i=1}^n D_i$.

Not all the states in D are physically possible. For example, consider an inverter described using three state variables: $OK \in \{true, false\}, input \in \{0,1\}$, and $output \in \{0,1\}$. The state $(true, 0, 0)$ is not realizable. Thus, there exist static constraints on the system, which define a subspace $SD \subseteq D$ of *possible* states.

Information referring to the system's dynamics. Events of several kinds can modify the current state of the system. First, these events can be part of the own dynamics of the system. For example, a flip-flop perpetually transits between two states. Second, events can correspond to the change of a component of the system from one behavior mode to another, e.g., from OK to abnormal. Third, external events can occur, which affect the system's state. For example, an external power breakdown prevents an electrical device from working.

We consider all these types of events on a common basis, as relations between two possible states of the system. If (s_1, s_2) belongs to such a relation (or event) e, it means that e may occur in state s_1, and that it might yield s_2 as a result. For instance, we might know that an inverter represented using the state variables given above has two failure modes: it shorts its output to its input or its output becomes stuck at 0. Then, the event of the inverter becoming abnormal would have $\big((true,1,0),(false,1,1)\big)$, $\big((true,1,0),(false,1,0)\big)$, and $\big((true,0,1),(false,0,0)\big)$ as members.

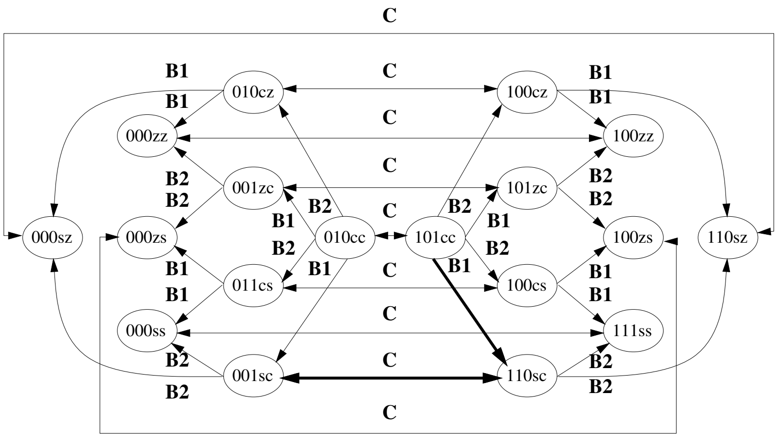
Using possible states and events as information, a system can then be viewed as a labeled directed graph whose nodes are the possible states of the system and whose arcs are labeled with events. In the rest of the paper, we refer to this graph as being the system's graph. Letting $\mathcal{R}(SD \times SD)$ denote the set of relations on $SD \times SD$, a system is formally defined as follows:

Def. 1 (System) *Given a vector of state variables $X = (x_1, \dots, x_n)$, with x_i ranging over D_i, a system is a pair $(SD, \mathcal{E})$, where*

- *$SD \subseteq \Pi_{i=1}^n D_i$ is the set of possible states of the system,*
- *$\mathcal{E} \subseteq \mathcal{R}(SD \times SD)$ is the set of events that can affect the system's state.*

Example Consider two inverters, I1 and I2, connected as in Figure 1. Each of them can be in one of the three following behavior modes: correct (noted c), shorting its output to its input (s), or stucking its output at zero (z). The vector $X_I = (\alpha_1, \alpha_2, \alpha_3, \beta_1, \beta_2)$ of state variables is used to represent the state of the system. $\alpha_1, \alpha_2, \alpha_3$ respectively represent the input of I1, the output of I1, and the output of I2; the αs range over $\{0,1\}$. β_1, resp. β_2, represents the behavior mode of I1, resp. I2; the βs range over $\{\mathsf{c},\mathsf{s},\mathsf{z}\}$. The possible states are those shown in Figure 1. The events are B1, resp. B2, which represents I1, resp. I2, breaking down, and C, which represents the input α_1 being changed. Note that B1 and B2 correspond to a change of the behavior mode of the system, that C is an external event, and that there is no event referring to the own dynamics of the system. In this example, faults are assumed to be permanent. We note SYS_I the corresponding system, whose graph is shown in Figure 1 (as a notational convention we will use a subscript I for names referring to construct of the two inverters example).

The definitions given in this paper are intentionally independent of the way their various components can be represented. For example, we prefer speaking of the traditional SD as a set of possible states of the system rather than as a set of formulae whose models represent the aforementioned states. In practice, an



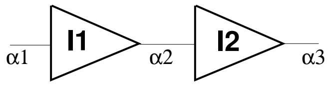


Figure 1: The System's graph for the Two Inverters

implicit representation of the system's graph must be adopted. In [2], we show how action formalisms as used in planning can provide a concise representation of knowledge about the system being diagnosed.

3 EVENT-BASED DIAGNOSIS

Given our definition of a system, we propose to define diagnoses as possible scenari (or sequences of events) that might have been followed by the system, so as to yield the observations gathered at successive time instants. Intuitively, a scenario represents a set of paths of the system's graph: those paths that are labeled with the sequence of events constituting the scenario. The scenario might lead from the starting state of one of these paths to its end state. All this is captured in the following definition.

Def. 2 (Scenario) *Let $SYS \equiv (SD, \mathcal{E})$ be a system. A scenario E for SYS is a (possibly empty) sequence $[e_1, e_2, \ldots, e_n]$ such that $e_i \in \mathcal{E}$ for all $i \in \{1, \ldots, n\}$. Note that an event may have multiple occurrences in a scenario. $|E|$ denotes the length of scenario E.*

A scenario $E : [e_1, \ldots, e_n]$ for SYS denotes the following relation on $SD \times SD$:

$$\begin{cases} \{(s_1, s_{n+1}) \mid \exists s_2 \in SD, \ldots, \exists s_n \in SD \ \textit{s.t.} \\ \qquad \forall i \in \{1, \ldots, n\}(s_i, s_{i+1}) \in e_i\} & \textit{if } |E| \geq 1 \\ I_{SD} & \textit{otherwise} \end{cases}$$

where $I_{SD} \equiv \{(s, s) \mid s \in SD\}$ denotes the identity relation on $SD \times SD$.

In the following, E for a scenario will denote, according to the context, either the corresponding sequence of events or the corresponding relation between starting states and end states.

Let $s_1 \in SD$ and $s_2 \in SD$ be two possible states. We say that a scenario E might lead from s_1 to s_2 iff $(s_1, s_2) \in E$. For instance, $[\mathsf{C}, \mathsf{B2}, \mathsf{B1}]$ is a scenario for SYS_I. It might lead e.g., from $(1, 0, 1, \mathsf{c}, \mathsf{c})$ to $(0, 0, 0, \mathsf{s}, \mathsf{z})$, from $(0, 1, 0, \mathsf{c}, \mathsf{c})$ to $(1, 0, 0, \mathsf{z}, \mathsf{s})$, and so on.

An event-based diagnosis problem is defined as follows.

Def. 3 (Event-Based Diagnosis Problem) *An event-based diagnosis problem given $m \geq 2$ successive observations, is a pair $(SYS, [OBS_1, \ldots, OBS_m])$, where*

- *$SYS \equiv (SD, \mathcal{E})$ is a system,*
- *$OBS_1 \subseteq SD, \ldots, OBS_m \subseteq SD$ are the sets of states the system has been observed to possibly be in at m successive instants.*

3.1 THE TWO OBSERVATIONS CASE

We first define an event-based diagnosis for the case where two observations are available, and generalize to m observations later. Given two successive observations, a diagnosis is a scenario that might lead from some possible state verifying the first observation to some possible state verifying the second. In terms of the system graph, a diagnosis given two observations is the label of a path leading from a state verifying the first observation to a state verifying the second observation.

Def. 4 (Event-Based Diagnosis) [given two successive observations] *An event-based diagnosis for $(SYS, [OBS_1, OBS_2])$ is a scenario E for SYS such that*

$$\exists s_1 \in OBS_1, \ \exists s_2 \in OBS_2 \ \ \textit{s.t.} \ \ (s_1, s_2) \in E.$$

(Recall that a scenario E defines a relation on $SD \times SD$). Note that the empty scenario is a diagnosis if and only if the two observations are consistent, i.e, iff $OBS_1 \cap OBS_2 \neq \emptyset$.

Example Consider the problem ψ_I for the two inverters, described as follows. Initially, the circuit, fed with input $\alpha_1 = 1$, has been tested and has been shown to be correct. Hence, $OBS_1 = \{(1, 0, 1, \mathsf{c}, \mathsf{c})\}$. Later on, it is known that $\alpha_1 = 1$ and $\alpha_3 = 1$. Hence,

$OBS_2 = \{(1,0,1,\mathsf{c},\mathsf{c}),(1,0,1,\mathsf{z},\mathsf{c}),(1,1,1,\mathsf{s},\mathsf{s})\}$. The diagnoses for ψ_I are $[], [\mathsf{B1}], [\mathsf{B1},\mathsf{B2}], [\mathsf{B2},\mathsf{B1}]$.

Using partially ordered sets of events instead of sequences of events would provide a more compact representation gathering the diagnoses that are compatible with the partial ordering. For sake of simplicity, the subsequent definitions will go on dealing with scenari. However, as a shorthand when dealing with examples, we will use the notation $\lceil e_1,\dots,e_n\rceil$ whenever events $e_1,\dots,e_n$ do not need to be ordered. In the above example, $[\mathsf{B1},\mathsf{B2}]$ and $[\mathsf{B2},\mathsf{B1}]$ are both diagnoses; we gather them into $\lceil \mathsf{B1},\mathsf{B2}\rceil$.

3.2 THE GENERAL CASE

We now generalize the previous definition to the case where more than two observations are available. We define an event-based diagnosis given m consecutive observations as the concatenation of $m-1$ event-based diagnoses given two consecutive observations. Two consecutive diagnoses in the concatenation must agree on intermediate states: the first diagnoses must possibly lead to a state from which the second diagnosis may start.

In the remainder of this paper, we use the following notation. Given two scenari $E_1 \equiv [e_{1,1},\dots,e_{1,n}]$ and $E_2 \equiv [e_{2,1},\dots,e_{2,m}]$ for the same system SYS, we note $E_1 \bullet E_2$ the concatenation of E_1 and E_2, i.e. $[e_{1,1},\dots,e_{1,n},e_{2,1},\dots,e_{2,m}]$. Note that this concatenation is also a scenario for SYS.

Def. 5 (Event-based Diagnosis) [given m successive observations] *An event-based diagnosis for $(SYS,[OBS_1,\dots,OBS_m])$, $m \geq 2$, is a scenario E for SYS such that*

$$E = E_1 \bullet \dots \bullet E_{m-1}, \text{ and}$$

$$\exists s_1 \in OBS_1,\dots,\exists s_m \in OBS_m \text{ s.t. } \forall i \in \{1,m-1\}\ (s_i,s_{i+1}) \in E_i.$$

Hence, a diagnosis given m consecutive observations, corresponds to a path in the system's graph which goes through intermediate states successively verifying the observations made at successive times.

Example Consider the problem ψ_I' for the two inverters, described as follows. Initially: as for ψ_I, $OBS_1 = \{(1,0,1,\mathsf{c},\mathsf{c})\}$. Second step: as for ψ_I, $OBS_2 = \{(1,0,1,\mathsf{c},\mathsf{c}),(1,0,1,\mathsf{z},\mathsf{c}),(1,1,1,\mathsf{s},\mathsf{s})\}$. The diagnoses obtained at this second step are $[], [\mathsf{B1}]$, and $\lceil \mathsf{B1},\mathsf{B2}\rceil$.

Third step: it is known that $\alpha_1 = 1$ and $\alpha_3 = 0$. Thus, $OBS_3 = \{(1,0,0,\mathsf{c},\mathsf{z}), (1,0,0,\mathsf{c},\mathsf{s}), (1,0,0,\mathsf{z},\mathsf{z}), (1,0,0,\mathsf{z},\mathsf{s}), (1,1,0,\mathsf{s},\mathsf{z}), (1,1,0,\mathsf{s},\mathsf{c})\}$. The empty diagnosis obtained at step 2 can be extended, which yields diagnoses $[] \bullet [\mathsf{B1}]$, $[] \bullet [\mathsf{B2}]$, and $[] \bullet \lceil \mathsf{B1},\mathsf{B2}\rceil$. Diagnosis $[\mathsf{B1}]$ obtained at step 2 can be extended to $[\mathsf{B1}] \bullet [\mathsf{B2}]$. As can be seen from Figure 1, diagnosis $\lceil \mathsf{B1},\mathsf{B2}\rceil$ obtained at step 2 cannot be extended. This

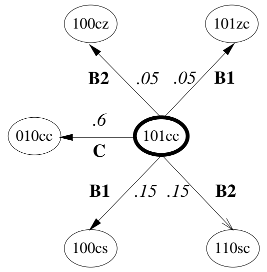


Figure 2: $p(s',e,(1,0,1,\mathsf{c},\mathsf{c}))$ for the Two Inverters.

is due to the fact that faults are assumed to be permanent in our example: once an inverter is in a failure mode, no event exists that enables getting out of this mode (e.g., there is no event enabling to get out from state $(1,1,1,\mathsf{s},\mathsf{s})$ which is the state to which $\lceil \mathsf{B1},\mathsf{B2}\rceil$ leads at step 2, and which doesn't verify OBS_3). In sum, at step 3, diagnoses $[\mathsf{B1}]$, $[\mathsf{B2}]$, and $\lceil \mathsf{B1},\mathsf{B2}\rceil$ are obtained.

Fourth step: it is known that $\alpha_1 = 0$ and $\alpha_3 = 1$, i.e., $OBS_4 = \{(0,0,1,\mathsf{z},\mathsf{c}),(0,0,1,\mathsf{s},\mathsf{c})\}$. Diagnosis $[\mathsf{B1}]$ obtained at step 3 can be extended to $[\mathsf{B1}] \bullet [\mathsf{C}]$ so as to account for the new observation. Diagnoses $[\mathsf{B2}]$ and $\lceil \mathsf{B1},\mathsf{B2}\rceil$ cannot be extended. In sum, the unique final diagnosis is $[\mathsf{B1},\mathsf{C}]$, and the path of the system's graph followed by the system is shown as bold transitions in Figure 1.

4 PREFERRED DIAGNOSES

Unless a system is highly stable (i.e., if a large number of states are permanent), an event-based diagnosis problem often has an infinite number of solutions. Even if this number is finite, it is necessary to express preferences among event-based diagnoses, which is the problem we address now.

4.1 MOST PROBABLE DIAGNOSES

When probabilistic information can be provided, it obviously makes sense to prefer diagnoses that, given the observations, are the most probable. In order to prefer most probable diagnoses in the general case (under the Markov assumption for our study, since the result of events only depend on the state they occur in), we must be provided with:

- given that we are in state s, the (relative) probability of leaving s by transiting to state s' via event e; this probability is noted $p(s',e,s)$, and must verify $\sum_{e \in \mathcal{E}} \sum_{s' \in SD} p(s',e,s) = 1$ for all states s that can be left; Figure 2 represents $p(s',e,(1,0,1,\mathsf{c},\mathsf{c}))$ for the two inverters example.
- the probability of s being the actual initial state, given that this initial state is in OBS_1, which we note $p(s,OBS_1)$; this probability must verify $\sum_{s \in OBS_1} p(s,OBS_1) = 1$.

From this, we can recursively define the probability $p(E, s, OBS_2)$ of scenario E occurring from state s and leading into a state in OBS_2 as follows:

$$p([], s, OBS_2) = \begin{cases} 1 & \text{if } s \in OBS_2 \\ 0 & \text{otherwise} \end{cases}$$
$$p(e \bullet E, s, OBS_2) = \sum_{s' \in SD} p(s', e, s)\ p(E, s', OBS_2)$$

Now, the probability of E occurring from a state in OBS_1 and leading to a state in OBS_2 is:

$$p(E, [OBS_1, OBS_2]) = \sum_{s \in SD} p(s, OBS_1)\ p(E, s, OBS_2) \quad (1)$$

In order to properly compute the probability of scenario E, i.e., the probability of E occurring from OBS_1 given that OBS_2 is observed, we would have to divide this result by the probability of OBS_2 being observed. In general, this probability can only be computed with some approximation. Since we only seek the correct determination of the probability ranking of each diagnosis, the denominator, which is just a normalization factor, does not need to be computed.

Equation (1) only applies to two observations. Its generalization $p(E, [OBS_1, \ldots, OBS_m])$ to multiple observations is straightforward and is given in [2].

4.2 OTHER PREFERENCE CRITERIA

Most of the time, probabilistic information cannot be provided, and more pragmatic preference criteria are used to discriminate between diagnoses. In [2], we show how several criteria (leading to shortest, minimal and least redundant diagnoses) can be naturally expressed in our framework and can be seen as an approximate measure of the probability of the diagnoses.

4.3 EXPLANATORY DIAGNOSES

In the event-based diagnosis framework, explanatory (or abductive) diagnoses are scenari that, if they occur, *necessarily* yield the observations. The definition of diagnoses (Definition 4) only requires a diagnosis to *possibly* lead to one of the states in OBS_2 from at least one state in OBS_1. In terms of the system's graph, this amounts to saying that there exists *some* path labeled with the diagnosis which starts from some state in OBS_1 and leads to some state in OBS_2. The diagnoses are then only consistent with the observations. In order to define explanatory diagnosis, we must further require that *every* path labeled with the diagnosis and starting from a state in OBS_1 leads to a state in OBS_2. In [2], we formally define explanatory diagnoses and give them a probabilistic account through what we call the *explicative power* of a diagnosis.

5 FUTURE AND RELATED WORK

In this paper, we have proposed to view the diagnosis task as the determination of the event-history of the system between successive observations. As more extensively stated in the introduction, this approach is particularly useful when explaining successive observations requires taking the history of the system into account. It allows precedence constraints between faults, as well as intermittent and non-intermittent faults to be modeled, and provides a unified representation and treatment of the various types of evolutions of the system's state: evolutions due to internal faults, to exogeneous events, as well as to test/repair actions.

The general framework presented in this paper has enabled us to formally define event-based diagnoses, independently of the way a system can be represented. Explicitly enumerating states in SD as well as the members of the relations capturing events, is not what we advocate. We clearly need adequate higher-level representations instanciating the general framework, such as action formalisms based on state-change operators. See [2] for details.

In [2], we discuss the similarities existing between event-based diagnosis and planning. Future work will concentrate on more carefully exploring these connections in particular with respect to benefiting from more expressive representations (e.g., representations involving numeric time, parallel events, partially ordered sets of events, and abstraction), to adapting planning algorithms so as to account for the specificity of the event-based diagnosis problem, and to exploiting the potential of the event-based framework for the generation of repair plans, especially when interleaved with the diagnosis process, as it is required for monitoring dynamic processes.

To conclude, let us compare our work to three types of related ones: work extending model-based diagnosis to evolutive systems, qualitative approaches, and situation recognition.

Within the first type of approaches, [6] advocates the extension of the consistency-based approach to the explicit use of time points. A diagnosis is a state of the system, accounting for different time points, which is consistent with the observations. This approach has the advantage of enabling the representation of both static and dynamic aspects of the system within the same logical formalism, but suffers from computational complexity. Our approach uses extra-logical state-change operators, which allows a more efficient way to diagnose a system by decoupling its static and dynamic behavior. In [6], temporal relationships such as delays between events and observations or numerical constraints can be expressed, which is not the case in our formalism. One perspective is to augment our basic framework by allowing the expression of such temporal constraints.

Decoupling atemporal and temporal diagnoses has already been proposed in [1]. The static part of the system is described by a set of first-order formulae (SD) and the atemporal diagnoses are obtained using the traditional techniques devoted to static systems. The dynamic part is represented by a set of Markovian transition graphs, each of which expresses the possible evolutions of a single component of the system. A temporal diagnosis is then a sequence of atemporal diagnoses obeying the transition constraints between states expressed by the transition graphs. A probabilistic reliability model is used to select the preferred diagnoses. This approach relies on the assumption that the global evolution of the system can be represented by the individual evolution of its components and that the components behaves independently, which is too restrictive in most cases. Moreover, the component-oriented representation is limited to internal changes and cannot account for external events or actions. In our approach, the dynamic part is expressed by a set of events which can correspond to components changing from a mode to another, but also to external spontaneous events or controlled actions. Another difference is that the definition of temporal diagnoses in [1] is component-oriented while our definition is event-oriented. A component-oriented definition is mainly justified when dealing with component-oriented repair actions. If it is often the case for static devices such as digital circuits, it is not always sufficient when dealing with complex processes, for which actions are decided according to the identified sequence of events, rather than according to the components and their state.

[7, 14] propose the use of planning techniques to interleave repair actions and observation actions during the diagnosis process. Our proposal, viewing diagnoses as sequences of events, seems to be adequate to get an unified framework in which controlled events, such as repair or observation actions, and spontaneous events can be integrated. Thus, our approach is open towards on-line model-based repair of evolutive systems.

Let us now turn to qualitative approaches. Qualitative modeling has mainly been used for the monitoring of dynamic systems as in [5, 11]. In these approaches, the possible evolutions of the system are represented by its qualitative states in a graph sharing some similarities with our system's graph. Changes of states are not expressed as explicit events but are produced by means of a qualitative simulation, which relies on the physical laws of the system and predicts the next states according to the own dynamics of the system. In our approach, the evolution of a system is represented in a more abstract way. Our aim is not to track the internal changes of the system by interpreting a flow of time-stamped observations, but to get a more repair-oriented view of an evolutive system.

Lastly, comparison can be made with situation recognition as proposed in [4], more dedicated to monitoring than strictly speaking to diagnosis. The system to be surveyed is described by the set of situation models (or scenari) of its normal and abnormal evolutions. A scenario corresponds to a set of elementary events (changes of values of observable features) with temporal constraints between them. The situation recognition system receives a stream of time-stamped observations as input, and recognizes an instance of a predefined scenario as this latter is developing. A first point to be noticed is that events are here micro-events, denoting the change of state of an observable feature. In our approach, an event is a macro-event, described by its preconditions and its effects. This latter level of abstraction is quite different and is dictated by the necessary adequation between the level of description of the events and that of the repair actions. Another point is that only predefined sequences of events can be recognized in the situation recognition approach. For combinatorial reasons, a complete set of such sequences can generally not be provided. The traditional remedy to this problem is to select scenari according to some a priori preferences. However, the drawback of this solution is that unpredicted events (surprises) cannot be taken into account. These problems are avoided with our approach, since the possible sequences of events explaining the observations are built and selected during the diagnosis process.

References

[1] L. Console, L. Portinale, D. Theseider Dupre, and P. Torasso. Diagnostic reasoning across different time points. In *Proc. ECAI-92*, pages 369–373, 1992.

[2] M.-O. Cordier and S. Thiébaux. Event-based diagnosis for evolutive systems. Research Report 819, IRISA, May 1994.

[3] J. de Kleer and B. Williams. Diagnosis with behavioral modes. In *Proc. IJCAI-89*, pages 1324–1330, 1989.

[4] C. Dousson, P. Gaborit, and M. Ghallab. Situation recognition: Representation and algorithms. In *Proc. IJCAI-93*, pages 166–172, 1993.

[5] D. Dvorak and B. Kuipers. Model-based monitoring of dynamic systems. In *Proc. IJCAI-89*, pages 1238–1243, 1989.

[6] G. Friedrich and F. Lackinger. Diagnosing temporal misbehaviour. In *Proc. IJCAI-91*, pages 1116–1122, 1991.

[7] G. Friedrich and W. Nejdl. Choosing observations and actions in model-based diagnosis-repair systems. In *Proc. KR-92*, pages 489–498, 1992.

[8] W. Hamscher. Modeling digital circuits for troubleshooting. *J. Artificial Intelligence*, 51:223–271, 1991.

[9] B. Kuipers. Qualitative simulation. *J. Artificial Intelligence*, 29:289–338, 1986.

[10] F. Lackinger and W. Nejdl. Integrating model-based monitoring and diagnosis of complex dynamic sytems. In *Proc. IJCAI-91*, pages 1123–1128, 1991.

[11] H. T. Ng. Model-based, multiple fault diagnosis of dynamic, continuous physical devices. *IEEE Expert*, 6(6):38–43, 1991.

[12] O. Raiman, J. de Kleer, and V. Saraswat. Exploiting non-intermittency. In *Proc. 1^{st} Int. Workshop on Principles of Diagnosis*, pages 120–123, 1990.

[13] R. Reiter. A theory for diagnosis from first principles. *J. Artificial Intelligence*, 32:57–95, 1987.

[14] Y. Sun and D. Weld. A framework for model-based repair. In *Proc. AAAI-93*, pages 182–187, 1993.