Using Causality and Actions for Diagnosis (Preliminary Report)

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Abstract

This paper introduces a theory of diagnosis for dynamic systems. System behavior is described in an action formalism. Diagnosing amounts to finding the history of the faults of the system that explain the observations after a sequence of actions. The solution to the diagnosis problem provides an explanation for what components have failed and when did.

Technically, the diagnosis problem is described by adding a condition to the rules affected by faults and it is solved with causality simultaneously with the solution to the frame and ramification problems.

Keywords: Diagnosis, Representations of Action.

1 Introduction

Since mid-eighties, diagnosis research has been focussed on logical approaches for diagnosis of static systems, known as *model-based diagnosis* (**MBD**). In these approaches, logical formulae are used to represent both the structure and the behavior of the target device and the observations of the system's operation. Typically, the model of the target device includes a special predicate denoting the correct or incorrect functioning of the device components, namely, $ab(c)$, abnormal component c.

There are two widely accepted approaches to logic-based diagnosis: *consistency-based diagnosis* (e.g., [11]) and *abductive diagnosis* (e.g. [2]). The first one is based on the notion of logical consistency whereas the second one is based on the notion of entailment.

In the last years, the attention of **MBD** community has been focussing on the diagnosis of systems that evolve [1]. In this field, several approaches have been followed (e.g. [9] and [12] in the field of actions theory, [3] in the field of event-based diagnosis and [5] in the field of qualitative reasoning). In this work, we present a theory of diagnosis for dynamic systems described with actions formalism. Our approach works with systems that evolve by means of actions performed by an external agent. The representation of the statics and dynamics of the system is done in a logical approach for reasoning about actions and change [10] and it includes an special fluent $ab(c)$ that accounts for the faulty behavior of a component.

The use of action formalisms for diagnosis are faced with the problem of how to define the nature of faults with the concepts of action formalisms. Initially there are two choices:

- if $ab(c)$ terms represent actions then the problem of diagnosis is a planning problem, i. e., finding a sequence of actions (faults) that leads to the observed situation. But these plans are generally non-minimal and then a further minimization of the plan is needed apart from the usual one in action formalisms to solve the frame and ramification problems. Furthermore planning in narrative and state-transition formalisms of actions is not deduction.
- if $ab(c)$ term represents fluents then the problem of diagnosis is an explanation problem. The minimization of the faults can be achieved at the same time and with the same minimization of the action formalism, so no additional minimization is needed. Furthermore the problem remains a deduction problem. But as long as $ab(c)$ terms are fluents they are abided to inertia law. So, solutions to explanation imply that the observations entail facts (faults) for the initial situation and then diagnosis is closer to static.

In this work, we have focussed on the second choice, but domain has been extended from static diagnosis to account for faults not only in the initial situation but in any situation of the narrative.

The rest of the paper is organized as follows. In the next section, we introduce the syntax and semantics of our logical approach. First, we expose the basic static case and then we extend it for narrative-based actions reasoning. In section 3, we establish our framework of diagnosis. Finally, in section 4, we comment related work in the literature.

2 Representation of dynamic systems

In this section we present a logical approach [10] for reasoning about action and change, in which causality is promoted to the category of an extra valuation of formulas, parallel to the classical truth valuation. Firstly, we formulate the syntax and semantics of L^2 in the basic static case. Finally, an elaboration of L^2, called AL^2, for narrative-based actions reasoning is presented.

2.1 L^2 Syntax and semantics

The nonmonotonic logic L^2 is a logical approach to deal with causal knowledge. This purpose has been achieved by introducing the concept of *pertinence* as an extra valuation of atoms. The syntax of L^2 is the classical propositional one plus the new conditional expressions:

$$\psi \Leftarrow \phi \tag{1}$$

being ϕ and ψ classical propositional formulas, and plus the new operator:

$$\mathit{pert}(a) \tag{2}$$

being a an atom.

The semantics consists in *two simultaneous* valuations. Apart from the usual truth value $\{\mathtt{t}, \mathtt{f}\}$, a formula will also be assigned a *pertinence* value: "pertinent" or "non-pertinent", denoted respectively as $\mathtt{p}$ and $\mathtt{n}$.

Definition 1 (L^2 interpretation) Given a signature $\mathcal{S}$, a L^2 *interpretation*, I, is a mapping $I : \mathcal{S} \longrightarrow \{\mathtt{t}, \mathtt{f}\} \times \{\mathtt{p}, \mathtt{n}\}$ assigning truth and pertinence to each atom. An interpretation I may be alternatively described by a pair $\langle S, P\rangle$ of sets of atoms, for representing truth and pertinence respectively:

$$\begin{array}{ll} I(q) \in \{\mathtt{tp}, \mathtt{tn}\} & \text{iff } q \in S \\ I(q) \in \{\mathtt{tp}, \mathtt{fp}\} & \text{iff } q \in P \end{array} \qquad \Box$$

Interpretations are extended to non-atomic formulae by a variation of standard structural induction, shown in Figure 1. There, ϕ^I stands for the pair of values that interpretation I assigns to formula ϕ. Also, variable α is used to represent any pertinence value and variable β is used to represent any truth value.

Truth for propositional formulas is interpreted in the classical way, whereas their pertinence is independently measured by checking whether any atom occurring in the formula is pertinent. Causal rules act as a pertinence propagation, reflecting how pertinence may affect to other pertinences. The truth of *pert*(a) states whether the atom a is pertinent or not, whereas its pertinence is taken form a, that is, if and only if a is pertinent then *pert*(a) is pertinent.

As in any multivalued logic, in order to define the concept of model, we will need to select a value to understand that a formula is satisfied. If nothing else is specified, we will assume that assigning any value from $\{\mathtt{tp}, \mathtt{tn}\}$, *satisfies* a formula, that is, it is enough with making it true. However, we sometimes will be interested in being more specific. To this aim, we adopt the notation $\phi\langle v\rangle$, where $v \in \{\mathtt{tp}, \mathtt{tn}, \mathtt{fp}, \mathtt{fn}, \mathtt{t}, \mathtt{f}, \mathtt{p}, \mathtt{n}\}$, to stand for "formula ϕ is satisfied if it is assigned value v."

An interpretation I is said to be a *model* of a theory T when it satisfies all the formulas in T, that is, it assigns

$$(\mathrm{pert}(a))^I = \begin{cases} \mathtt{fn} & \text{if } a^I = \beta\mathtt{n} \\ \mathtt{tp} & \text{if } a^I = \beta\mathtt{p} \end{cases}$$

$$(\neg\phi)^I = \begin{cases} \mathtt{t}\alpha & \text{if } \phi^I = \mathtt{f}\alpha \\ \mathtt{f}\alpha & \text{if } \phi^I = \mathtt{t}\alpha \end{cases}$$

$$(\psi \Leftarrow \phi)^I = \begin{cases} \mathtt{tn} & \text{if } \phi^I \neq \mathtt{tp} \\ \mathtt{fn} & \text{if } \phi^I = \mathtt{tp} \text{ and } \psi^I \neq \mathtt{tp} \\ \mathtt{tp} & \text{otherwise} \end{cases}$$

$(\phi \wedge \psi)^I$	fn	fp	tn	tp
fn	fn	fp	fn	fp
fp	fp	fp	fp	fp
tn	fn	fp	tn	tp
tp	fp	fp	tp	tp

$(\phi \vee \psi)^I$	fn	fp	tn	tp
fn	fn	fp	tn	tp
fp	fp	fp	tp	tp
tn	tn	tp	tn	tp
tp	tp	tp	tp	tp

Figure 1: Interpretation of a formula.

to each formula its selected value. A set of formulas T *entails* a formula ϕ, if all the models of T are models of ϕ.

This basic monotonic framework must be extended to capture the default: "any atom should be only pertinent when there exists some evidence for that." The following definitions capture this idea:

Definition 2 ($\leq_{\mathtt{p}}$) Given two L^2 interpretations $I = \langle S, P\rangle$ and $I' = \langle S', P'\rangle$, we say that I is lower than I', $I \leq_{\mathtt{p}} I'$, iff $S = S'$ and $P \subseteq P'$. $\Box$

Definition 3 (L^2 selected model) A model $I = \langle S, P\rangle$ of a theory T is said to be a *selected model* iff it is a minimal model, with respect to the $\leq_{\mathtt{p}}$ ordering relation. $\Box$

Example 1 We have a very simple digital circuit composed by only one *and* gate and with inputs x and y. We just put to 1 the x input and we know that y is 1. $\Box$

The theory $T = \{\mathit{and\_gate} \Leftarrow x \wedge y, \neg\mathit{and\_gate} \Leftarrow \neg(x \wedge y)\}$ represents the digital circuit. We extend this theory with the facts: $\{x\langle\mathtt{tp}\rangle\}$, that acts like an *action* or a primary cause, and $\{y\langle\mathtt{t}\rangle\}$, saying that input y is true but its pertinence is unknown. Theory $T \cup \{x\langle\mathtt{tp}\rangle, y\langle\mathtt{t}\rangle\}$ has two models: $\{\mathit{and\_gate}\langle\mathtt{tp}\rangle, x\langle\mathtt{tp}\rangle, y\langle\mathtt{tp}\rangle\}$ and $\{\mathit{and\_gate}\langle\mathtt{tp}\rangle, x\langle\mathtt{tp}\rangle, y\langle\mathtt{tn}\rangle\}$, but only the last one is a L^2 selected model.

2.2 AL^2 Syntax and semantics

In this section we extend the L^2 logic for narrative-based actions reasoning, called AL^2. From a syntactical point of view, AL^2 is just a specialization of L^2, separating the signature into two disjoint sets: the set $\mathcal{F}$ of *fluent* *names* and the set $\mathcal{A}$ of *action names*. Atoms will have the shape q_t where q is either a fluent or an action name and t is a non-negative integer ranging from 0 to the number of situations in the narrative, in a similar way to [8]. A causal rule $F \Leftarrow \phi$ in AL^2 must satisfy two new syntactic restrictions: (1) F must have the shape f_i or $\neg f_i$ (for some fluent f), and (2) there cannot occur a subindex $j > i$ in ϕ.

Typically, an AL^2 domain description will consist of two sets of formulas $\langle B, O\rangle$: the set B called *background knowledge* which contains causal rules, and the set O of *observations* which are non-causal formulas.

Pertinence of actions can be captured now by the axiom schemata:

$$a_t\langle \mathtt{p}\rangle \tag{3}$$

for any action $a \in \mathcal{A}$. Persistence of non-pertinent fluents is represented by the inertia law:

$$\neg f_t\langle \mathtt{p}\rangle \supset (f_t \equiv f_{t-1}) \tag{4}$$

for any fluent f and for $t > 0$. The inertia law is imposed *outside* the minimization for selected models, applying a *filter preferential entailment* technique.

Definition 4 (Causal model) A model I of a theory T is said to be *causal* iff it is a selected model of T and satisfies the inertia law schema (4). □

In other words, causal models correspond to the theory obtained by parallel circumscription [6]:

$$\mathrm{CIRC}[T;\ q^1\langle \mathtt{p}\rangle, q^2\langle \mathtt{p}\rangle, \ldots, q^n\langle \mathtt{p}\rangle;] \cup (4)$$

being q^i all the subindexed atoms for actions and fluents.

Example 2 (the yale shooting scenario) We have a gun and we want to kill a turkey. There are two possible actions loading and shooting the gun. The Turkey will be dead only if we shoot with the gun previously loaded. □

The AL^2 formulation of this example consists of a set of actions $\mathcal{A} = \{\mathit{shoot}, \mathit{load}\}$, a set of fluents $\mathcal{F} = \{\mathit{dead}, \mathit{loaded}\}$ and a set B of causal rules:

$$\begin{aligned} \mathit{loaded}_t &\Leftarrow \mathit{load}_t \\ \mathit{dead}_t &\Leftarrow \mathit{loaded}_{t-1} \wedge \mathit{shoot}_t \end{aligned}$$

Let us study the case where we load the gun and then we shoot. This is captured by the observation.

$$\neg \mathit{loaded}_0 \wedge \neg \mathit{dead}_0 \wedge \mathit{load}_1 \wedge \mathit{shoot}_2$$

With this observation we obtain as unique causal model:

$$\begin{aligned} \{&\mathit{loaded}_1, \mathit{loaded}_1\langle \mathtt{p}\rangle, \neg \mathit{dead}_1, \neg \mathit{dead}_1\langle \mathtt{p}\rangle, \\ &\mathit{loaded}_2, \neg \mathit{loaded}_2\langle \mathtt{p}\rangle, \mathit{dead}_2, \mathit{dead}_2\langle \mathtt{p}\rangle\} \end{aligned}$$

3 Diagnosis of Dynamic Systems

The logical framework introduced in the previous section is the basis for the description of the statics and dynamics of a system. In this section we provide a characterization of consistency-based diagnosis of dynamic systems by means of the logical models of AL^2 theories.

Our approach is based in the consideration of the diagnosis of dynamic systems as an explanation problem, in the sense that the faulty components are entailed by the theory. But this approach suffers from the problem of how to diagnose that some component failed from a particular moment, and not that it has failed from the beginning. The diagnosis problem for action domains is solved with causality defining $ab(c)$, and adding a condition to the rules affected by faults in the form $\ldots \wedge \neg \mathit{pert}(ab(c))$. Formula $\neg \mathit{pert}(ab(c)_t)$ acts as a condition that allows —under malfunctioning conditions— to disable causal rules and then explain the abnormal behavior of the components. The minimization of pertinence done by L^2 also minimizes $ab(c)$—a fault exists when $ab(f)$ is pertinent—and the *causal contraposition* of the rule entails the pertinence of the $ab(c)$ needed for the diagnosis—though $ab(c)$ is not the head of any formula in the theory.

Let us study the formalization of the following example in order to show clearly the ideas aforementioned:

Example 3 (the galician shooting scenario) The gun of example (2) has two distinguishable components: a trigger and a drum. The gun is loaded only if the drum does not fails when we load the gun. The turkey is not dead after shooting with a loaded gun if the trigger fails. □

The AL^2 formulation of this example consists of a set of actions $\mathcal{A} = \{\mathit{shoot}, \mathit{load}\}$, a set of fluents $\mathcal{F} = \{\mathit{loaded}, \mathit{dead}, ab(\mathit{drum}), ab(\mathit{trigger})\}$ and a set B of causal rules:

$$\begin{aligned} \mathit{loaded}_t &\Leftarrow \mathit{load}_t \wedge \neg \mathit{pert}(ab(\mathit{drum})_t) && (5) \\ \mathit{dead}_t &\Leftarrow \mathit{loaded}_{t-1} \wedge \mathit{shoot}_t \wedge \neg \mathit{pert}(ab(\mathit{trigger})_t) && (6) \end{aligned}$$

Our approach uses the special $ab(c)$ fluents in order to express the possibility of a component failure, but the failure is detected when some of these fluents become pertinent not matter their truth value. So, we can obviate the truth of these fluents without loss of generality.

Let us study the causal contraposition to disable causal rules, by considering the causal rule (5). If we perform action load_t and observe $\neg \mathit{loaded}_t$ then $ab(\mathit{drum})_t$ must be not pertinent because, otherwise, the conditions of the causal rule would be satisfied and this would lead to an inconsistency. So, a diagnosis is a set of pertinent instances of ab fluents. As a result, when selected models of AL^2 are calculated by $\mathrm{CIRC}[T;\ q^1\langle \mathtt{p}\rangle, q^2\langle \mathtt{p}\rangle, \ldots, q^n\langle \mathtt{p}\rangle;]$, models with non-minimal abnormalities are ruled out. So, the solution to the frame and ramification problem in our formalism provides the solution for diagnosis.

Following with example (3), let us study the case where we load the gun, shoot and then observe that the turkey is not dead. This is captured by the observation:

$$\begin{aligned} &\neg \mathit{loaded}_0 \wedge \neg \mathit{dead}_0 \wedge \mathit{load}_1 \wedge \neg \mathit{shoot}_1 \\ &\wedge \mathit{shoot}_2 \wedge \neg \mathit{load}_2 \wedge \neg \mathit{dead}_2 \end{aligned} \tag{7}$$

This observation gives us a description of the initial state, the actions performed and some resulting fluents.

The AL^2 theory consisting in the background knowledge B={(5),(6)} plus the observation (7) has two causal models:

$$\begin{aligned} d_1 = \{&loaded_1, loaded_1\langle \mathtt{p}\rangle, \neg dead_1, \neg dead_1\langle \mathtt{p}\rangle,\\ &\neg ab(drum)_1\langle \mathtt{p}\rangle, \neg ab(trigger)_1\langle \mathtt{p}\rangle, loaded_2,\\ &\neg loaded_2\langle \mathtt{p}\rangle, \neg ab(drum)_2\langle \mathtt{p}\rangle, ab(trigger)_2\langle \mathtt{p}\rangle\}\\ d_2 = \{&\neg loaded_1, \neg loaded_1\langle \mathtt{p}\rangle, \neg dead_1, \neg dead_1\langle \mathtt{p}\rangle,\\ &ab(drum)_1\langle \mathtt{p}\rangle, \neg ab(trigger)_1\langle \mathtt{p}\rangle, \neg loaded_2,\\ &\neg loaded_2\langle \mathtt{p}\rangle, \neg ab(drum)_2\langle \mathtt{p}\rangle, \neg ab(trigger)_2\langle \mathtt{p}\rangle\}\end{aligned}$$

Each one of these causal models yields a minimal diagnosis. In model d_1, the *drum* was faulty and the gun was not loaded, explaining in this way that the turkey was not dead. Model d_2 accounts for the turkey to be alive by the fault of the *trigger* in situation 2. As it can be seen, our diagnosis framework accounts for both *what* happens to the system and *when* it does. That is, the failure of the *drum* is only an explanation for an alive turkey if it happens in situation 1. If we add $loaded_1$ to (7) then the only explanation is that the *trigger* was abnormal in situation 2.

Note that the pertinence of $ab(c)$ fluents does not persist from one situation to another. A fluent $ab(c)$ is only pertinent when it explains the observation. As a result, our approach allows intermittent faults to be modeled. For instance, if we add to observation (7), a new situation 3 where we shoot again and the turkey dies:

$$\begin{aligned} &\neg loaded_0 \wedge \neg dead_0 \wedge load_1 \wedge \neg shoot_1 \\ &\wedge shoot_2 \wedge \neg load_2 \wedge \neg dead_2 \\ &\wedge shoot_3 \wedge \neg load_3 \wedge dead_3 \end{aligned} \tag{8}$$

then we obtain a single causal model:

$$\begin{aligned} d_1 = \{&loaded_1, loaded_1\langle \mathtt{p}\rangle, \neg dead_1, \neg dead_1\langle \mathtt{p}\rangle,\\ &\neg ab(drum)_1\langle \mathtt{p}\rangle, \neg ab(trigger)_1\langle \mathtt{p}\rangle, loaded_2, \neg loaded_2\langle \mathtt{p}\rangle,\\ &\neg ab(drum)_2\langle \mathtt{p}\rangle, ab(trigger)_2\langle \mathtt{p}\rangle, loaded_3, \neg loaded_3\langle \mathtt{p}\rangle,\\ &\neg ab(drum)_3\langle \mathtt{p}\rangle, \neg ab(trigger)_3\langle \mathtt{p}\rangle\}\end{aligned}$$

In this model the *trigger* fails intermittently in situation 2 to justify an alive turkey but in situation 3 the trigger is not faulty and the turkey dies.

Let us now to formalize these intuitive concepts. For this purpose we extend the notation of [4].

Definition 5 (System Description) A *system description SD* is a tuple $(\mathcal{F}, \mathcal{A}, B)$ consisting in a set of fluents $\mathcal{F}$, a set of actions $\mathcal{A}$ and a set of causal rules B. □

Definition 6 (Diagnosis Problem) A *diagnosis problem DP* is a tuple (*SD*, *OBS*, *COMPS*), where *SD* is the system description, *OBS* is a non causal formula and *COMPS* is the set of system components. □

In example (3) the set of components is obviously $COMPS = \{drum, trigger\}$.

Definition 7 (AB_i-hypothesis) Given two mutually exclusive sets of components $\Delta_1, \Delta_2 \subseteq COMPS$ and $\Delta_1 \cup \Delta_2 = COMPS$, define an AB_i-hypothesis $\mathcal{D}_i(\Delta_1, \Delta_2)$ with respect to situation i to be the conjunction:

$$[\bigwedge_{c\in\Delta_1} ab(c)_i\langle \mathtt{p}\rangle] \wedge [\bigwedge_{c\in\Delta_2} \neg ab(c)_i\langle \mathtt{p}\rangle]$$

□

Definition 8 (AB-hypothesis) Given n AB_i-hypothesis $\mathcal{D}_0(\Delta_1^0, \Delta_2^0), \cdots, \mathcal{D}_{n-1}(\Delta_1^{n-1}, \Delta_2^{n-1})$, define an AB-hypothesis $\mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1})$ for a narrative of n situations to be the conjunction:

$$\bigwedge_{i=0\cdots n-1} \mathcal{D}_i(\Delta_1, \Delta_2)$$

□

Definition 9 (Consistency-based Diagnosis) An AB-hypothesis $\mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1})$ is a consistency-based diagnosis **CBD** for a diagnosis problem DP = (*SD*, *OBS*, *COMPS*) iff the theory

$$< SD, OBS \cup \mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1}) >$$

is satisfiable. □

Lemma 1 *If M is a causal model of an* AL^2 *theory and M is a causal model of an* AL^2 *theory T' also, then M is a causal model of the* AL^2 *theory $T \cup T'$* □

This lemma is necessary for the proof of the next result. The proof is straightforward and it will be omitted.

Theorem 1 *Every causal model of the* AL^2 *domain description* $T =< \mathrm{SD}, \mathrm{OBS} >$ *yields a consistency-based diagnosis for the diagnosis problem* $\mathrm{DP} = (\mathrm{SD}, \mathrm{OBS}, \mathrm{COMPS})$.

Proof *Let $\mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1})$ be an AB-hypothesis built from a causal model M of* $T =< \mathrm{SD}, \mathrm{OBS} >$. *Let us assume that $\mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1})$ is not a consistency-based diagnosis for* $\mathrm{DP} = (\mathrm{SD}, \mathrm{OBS}, \mathrm{COMPS})$ *then* $T' =< \mathrm{SD}, \mathrm{OBS} \cup \mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1}) >$ *is no satisfiable. But M is a model of T and obviously by construction M is a model of $\mathcal{D}(\mathcal{D}_0, \cdots, \mathcal{D}_{n-1})$, so M must be a model of T'.* □

This theorem provides an interesting relation between consistency-based diagnosis and causal models of AL^2. Furthermore, causal models represent diagnoses with less $ab(c)_t\langle \mathtt{p}\rangle$ corresponding to the same truth and pertinence assignment for the other fluents. Characterizing diagnosis through causal models we intuitively give a new notion of minimal diagnosis that we have called *causal diagnosis*.

4 Discussion and related work

The relation between actions theory and diagnosis has been studied in literature by [12] and [9].

Thielscher has also studied the problem of diagnosis with actions. He solves the diagnosis problem as an explanation problem in a similar way to our approach. But his diagnosis is a regular explanation in the sense that observations are explained from an assumption of abnormalities at the initial situation. Thielscher extends his description in order to obtain faults in situations other than the initial one. For this purpose he includes in the description dependences among abnormalities (faulty behavior).

In our formalism the initial situation can be free of abnormalities, but they appear latter in any other situation. We achieved this result because the contraposition also acts as a ramification of the observations. Furthermore this ramification is not regular ramification because the pertinence of abnormal is entailed from the nonpertinence of the observations. This is a property of our formalism that defines causality while keeping other properties of logic-based formalisms, such as contraposition. Other logic-based formalisms for causality as Lin's one [7] do not manifest this contraposition because he does not mandatorily require that conditions be caused. So our approach is not directly applicable in Lin's formalism, but it remains to further study whether a similar approach can be defined in it.

McIlraith uses successor state axioms in the framework of Situation Calculus and the diagnosis problem is restricted to *stratified* theories. She solves the diagnosis problem as a problem of planning with constraints and an incomplete initial situation. This approach is similar to ours in that abnormalities appear in situations other than the initial one. But the minimization for inertia is not used to minimize diagnosis. Furthermore, we do not deduce new additional situations but more pertinent $ab(c)$ for the known situations.

Another interesting related work is [3]. They present a *event-based* diagnosis for dynamic systems that accounts for determining the sequence of *events* occurred between successive observations. In this sense their work is more related to that of McIlraith in *explanaroty diagnosis* than to ours. The main difference is in the formalization of the domain. Cordier et al. appeals to explicit transition systems to represent the dynamic systems and does not address the frame and ramification problems.

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