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Abstract

The paper analyzes the use of a Multi Agent System for Model Based Diagnosis. In a large dynamical system, it is often infeasible or even impossible to maintain a model of the whole system. Instead, several incomplete models of the system have to be used to detect possible faults. These models may also be physically be distributed.

A Multi Agent System of diagnostic agents may offer solutions for establishing a global diagnosis. If we use a separate agent for each incomplete model of the system, establishing a global diagnosis becomes a problem cooperation and negotiation between the diagnostic agents. This raises the question whether `a set of diagnostic agents, each having an incomplete model of the system, can (efficiently) determine the same global diagnosis as an ideal single diagnostic agent having the combined knowledge of the diagnostic agents?'

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1 Introduction

A traditional diagnostic tool can be viewed as a single *diagnostic agent* having a model of the whole system to be diagnosed. There are, however, several reasons why such a single agent approach may be inappropriate. First of all, if the system is physically distributed and large, there may be not enough time to compute a diagnosis centrally and to communicate all observations. Secondly, if the structure of the system is dynamic, it may change too fast to maintain an accurate global model of the system over time. Finally, sometimes the existence of an overall model is simply undesirable. For example, if the system is distributed over different legal entities, one entity does not wish other entities to have a detailed model of its part of the system. Examples of such systems are modern telecommunication networks, dynamic configuration of robotic systems such as AGV driving in a platoon, and so on. For such systems, a *distributed* approach of multiple diagnostic agents might offer a solution.

An important question is of course whether a set of diagnostic agents can (efficiently) determine the same global diagnosis as an ideal single diagnostic agent having the combined knowledge of the diagnostic agents?

To investigate this problem we distinguish two ways in which the model (knowledge) is distributed over the agents (cf. [4]): (1) *spatially distributed*: knowledge of system behavior is distributed over the agents according the spatial distribution of the system's components, and (2) *semantically distributed*: knowledge of system behavior is distributed over the agents according to the type of knowledge. An example of the latter distribution of knowledge is a separate model of the electrical and of the thermodynamical behavior of the system.

The way the knowledge is distributed turns out to have significant repercussion on multi-agent diagnosis[1].

Though multi-agent diagnosis turns out to be possible in theory, it is not always feasible. In this paper we will concentrate on the question whether a set of diagnostic agents can (efficiently) determine the same global diagnosis as an (ideal) single diagnostic agent having the combined knowledge of the diagnostic agents?

This paper is organized as follows. Section 2 specifies the diagnostic problem and Section 3 gives the standard diagnostic definitions. Section 4 discusses multi agent diagnosis. Section 5 concludes the paper.

2 The diagnostic setting

A system to be diagnosed is a tuple $S = (C, M, Sd, Ctx, Obs)$ where C is a set of components, $M = \{M_c \mid c \in C\}$ is a specification of possible fault modes per component, Sd is the system description, Ctx is a specification of inputs of the system that are determined outside the system by the environment and Obs is a set of observed values of the system. A component $c \in C$ is either a physical component or a subsystem that is considered as a component. A component in C has a normal mode $nor \in M_c$, one general fault mode $ab \in M_c$ and possibly several specific fault modes. Each component has a number

[1]Although we distinguish spatially and semantically distributed models, combinations are also possible.

of *connection points*. We use the predicate $cpnt(x, c)$ to denote that x is a connection point of component c.

A connection point has one or more values. The function $value(p, t)$ is used to denote the value of type t of a connection point p. Types are used to distinguish, for instance, between the voltage and the current of a connection point.[2]

Components can be connected through their connection points. These connections between components are given by instances $con(x, y)$ of a predicate $con(,)$ where x and y are connection point identifiers. The set Str of instances of the predicate con constitutes the *structural description* of the system.

The system description $Sd = Str \cup Beh$ consists of a structural description and a behavioral description for each component $Beh = \bigcup_{c \in C} Beh_c$. The set Beh_c specifies a behavior for each (fault) mode in M_c of a component c. In this specification, the predicate $mode(c, m)$ is used to denote the mode $m \in M_c$ of a component c. For each instance of $mode(,)$, Beh_c contains a behavioral description of the form: $mode(c, m) \to [\ldots]$ where $m \in M_c$.[3] The expression $[\ldots]$ describes the component's behaviour given its mode $m \in M_c$. It constrains the values the component's connection points may take.

The set Ctx describes the values of connection points that are determined by the environment. It consists of instances of the form $value(p, t) = v$ where p is a connections point, t is a value type and v is a value.

Finally, the set Obs describes the values of connection points that are observed (measured) by the diagnostic agent. It also consists of instances of the form $value(p, t) = v$ where p is a connections point, t is a value type and v is a value.

Given a system $S = (C, M, Sd, Ctx, Obs)$, a *candidate diagnosis* D for S is an assignment of modes to components that explains the observed behaviour of the system according to our diagnostic definition, to be discussed in the next section. A candidate diagnosis is specified by a set D of instances of the predicate $mode$ such that for every component $c \in C$ there is exactly one mode in $m \in M_c$ such that $mode(c, m) \in D$.

Note that there can be more than one diagnosis, only one of which gives the correct explanation. The latter is called the final diagnosis.

3 Single agent diagnosis

In this section we present some well-known concepts in model-based diagnosis. It will be called *single agent diagnosis* since it assumes that a single agent, having complete knowledge of the system, $S = (C, M, Sd, Ctx, Obs)$, suffices to make a diagnosis.

The diagnostic definition Given a system $S = (C, M, Sd, Ctx, Obs)$, a diagnosis can be made. In the literature two types of diagnoses are distinguished: *consistency based* [6, 7] and *abductive* [1] diagnosis. Both can be combined into one more general diagnostic definition [2]. This definition will be used here:

[2]It is not always convenient to introduce separate connection points for each value type that can be observed on one physical connection point.

[3]Note that we may use a single description for a class of components. Instances of this description must imply the form of description give here.

Definition 1 *Let $S = (C, M, Sd, Ctx, Obs)$ be the system to be diagnosed. Let Obs_{con}, $Obs_{\mathrm{abd}} \subseteq Obs$ be two subsets of the observations and let D be a candidate diagnosis. Then D is a diagnosis for S iff*

$$D \cup Sd \cup Ctx \mid\!\sim \bigwedge_{\varphi \in Obs_{\mathrm{abd}}} \varphi \text{ and } D \cup Sd \cup Ctx \cup Obs_{\mathrm{con}} \not\mid\!\sim \bot.$$

Note that we use the symbol $\mid\!\sim$ to denote the possibly limited reasoning capabilities of a diagnostic system. I.e $\{\varphi \mid \Sigma \mid\!\sim \varphi\} \subseteq \{\varphi \mid \Sigma \vdash \varphi\}$.

If $Obs_{\mathrm{abd}} = \varnothing$, then we have a pure consistency-based diagnosis, and if $Obs_{\mathrm{con}} = \varnothing$, we have a pure abductive diagnosis. Note that, in general, an abductive diagnostic agent is stronger than a consistency-based diagnosis.

Besides pure consistency based and abductive diagnosis, there is another interesting special case. In the absence of fault models, usually consistency based diagnosis is used since we cannot explain *abnormal observations*; i.e. the observations that do not correspond with the predicted values in case of no component failures. We can improve consistency based diagnosis if we also allow for abductive diagnosis [8]. In the absence of fault models, we can only give an explanation for the normal observations Obs_N; i.e. the observations that correspond with the predicted values in case of no component failures. This additional information can help us to reduce the number of candidate diagnoses, especially if it is safe to assume that the effects of one fault cannot be compensated by the effects of other faults.

The number of diagnoses Potentially, there can be an exponential number of diagnoses. Even for relatively small systems, listing all these diagnoses can be infeasible. In a well designed system it is unlikely that the many components fail at the same time (unless there is a cascade of failures). So, it is safe to assume that only a minimal number of components is broken. Hence, we can order the diagnoses with respect to the number of broken components. We can look for either diagnoses with a *minimum* number or with a *subset-minimal* number of broken components. Here we choose the latter.

Definition 2 *Let D and D' be two diagnoses. D is less than D', $D \prec D'$, iff $\{c \mid mode(c, ab) \in D\} \subset \{c \mid mode(c, ab) \in D'\}$. A diagnosis D is* minimal *iff for no diagnosis D' it holds that $D' \prec D$.*

Minimal diagnoses have a property that enable them to characterize a whole set of diagnoses [5]. This property turns out to be useful if we need to combine the diagnoses made by several agents:

Proposition 1 *Suppose that for each component $c \in C$ there are exactly two modes, nor and ab, and let $D \prec D'$ be two candidate diagnoses. Then D' is a pure consistency based diagnosis of a system if D is.*

This is a nice result since it enables us to characterize an exponential number of diagnoses. Especially if the number of faults is bounded by a constant or of the order $\mathcal{O}(\log(|C|))$, the number of minimal diagnoses is polynomial in $|C|$.

Partial diagnoses are another way to avoid listing an exponential number of diagnoses. In a partial diagnosis the mode of some of the components $c \in C$ is left undefined:

Definition 3 *Let D' be some candidate diagnosis. Then $D \subseteq D'$ is a partial diagnosis.*

We are of course interested in the smallest set, with respect to $\subset$, of components such that the corresponding partial diagnoses characterize a set of diagnoses. This partial diagnosis is called a *kernel diagnosis* [5].

Definition 4 *D is a* kernel diagnosis *of a system iff (1) D is a partial diagnosis such that every candidate diagnosis $D' \supseteq D$ is a diagnosis of the system, and (2) for no partial diagnosis $D'' \subset D$ the first item holds.*

Definition 5 *D is an abductive kernel diagnosis iff D is a minimal partial diagnosis such that: $D \cup Sd \cup Ctx \mid\!\sim \bigwedge_{\varphi \in Obs_{\mathrm{abd}}} \varphi$.*[4]

Definition 6 *D is a consistency based kernel diagnosis if and only if D is a minimal partial diagnosis such that: $D \cup Sd \cup Ctx \cup Obs_{\mathrm{con}} \not\mid\!\sim \bot$.*[5]

We can derive the kernel diagnoses for consistency based diagnosis with abductive explanation of normal observations from the two types of kernel diagnoses defined above.

Proposition 2 *Let D^{abd} be an abductive kernel diagnosis and let D^{con} be a consistency based kernel diagnosis of a system. Then, $D = D^{abd} \cup D^{con}$ is a kernel diagnosis that characterizes consistency based diagnosis with abductive explanation of normal observations if D is a partial diagnosis.*[6]

Proposition 3 *Let D be a kernel diagnosis that characterizes consistency based diagnosis with abductive explanation of normal observations.*

Then $D^{abd} = \{mode(c, nor) \mid mode(c, nor) \in D\}$ is an abductive partial diagnosis and $D^{con} = \{mode(c, ab) \mid mode(c, ab) \in D\}$ is a consistency based kernel diagnosis.

4 Multi agent diagnosis

Suppose that instead of one diagnostic agent, we have two or more diagnostic agents. What can we say about the ability of this group of agents to make a diagnosis. We will only consider cases in which we have two diagnostic agents since any case in which we have $n > 2$ diagnostic agents is a trivial extension. We assume that both agents, A_1 and A_2, have partial knowledge about the system. Let $C = C_1 \cup C_2$, let $Sd = Sd_1 \bigcup Sd_2$ and let $Obs = Obs_1 \bigcup Obs_2$. We also assume that agent knows the connections with the other agent; i.e. $con(x, y) \in Sd_i$ iff $cpnt(x, p), cpnt(y, q) \in Sd$, and $p \in C_i$ or $q \in C_i$. From this the agent can derive the corresponding connection points of the other agent; i.e. $Ex_i = \{x \mid con(x, y) \in Sd_i, \{cpnt(x, c), cpnt(y, c')\} \subseteq Sd, (c' \notin C_i \text{ or } c \notin C_i)\}$. The agent may have to ask / tell the values of connection points in Ex_i from / to the other agent.[7] So, $S_i = (C_i, M, Sd_i, Ctx, Obs_i)$ is the system known to agent A_i and Ex_i are the external connection points of S_i. Finally, let D_i be a candidate diagnosis of agent A_i.

[4]Note that all mode descriptions in D have the *normal* mode if $Obs_{abd} = Obs_N$. Also note that there is only one kernel diagnosis if none of the components behaves like a switch [8].

[5]Note that without fault models all mode descriptions in D have the *abnormal* mode.

[6]That is, D is a partial diagnosis if there are no *mode* conflicts; i.e. for no $c \in C$: $mode(c, no)$, $mode(c, ab) \in D$.

[7]Note that in case of more that 2 agents, agent A_i also need to know which agent is responsible for a connection point in Ex_i.

Given multiple diagnostic agents, an important question is how the diagnoses of the agents relate to the diagnoses of a single agent that has complete knowledge of the system description and the observations. When addressing this question we assume through out the paper that there are no conflicts between the knowledge of the different agents. That is, there is a diagnosis D such that: $D \cup Sd \cup Cxt \cup Obs$ is consistent.

Proposition 4 *Let A_1 and A_2 be two diagnostic agents each having partial knowledge of the system; i.e. S_1 and S_2. Moreover, let D be a single agent diagnosis of S.*

Then $D_1 = \{mode(c, s) \mid c \in C_1, mode(c, s) \in D\}$ is a diagnosis of A_1 and $D_2 = \{mode(c, s) \mid c \in C_2, mode(c, s) \in D\}$ is a diagnosis of A_2.

Proposition 5 *Let A_1 and A_2 be diagnostic agents with partial knowledge S_1 respectively S_2. Moreover, let D_1 and D_2 be diagnoses of agent A_1 respectively A_2 for which the agents agree on the values of the connection points Ex_1 and Ex_2.*

Then, $D = D_1 \cup D_2$ is a single-agent diagnosis if D is a candidate diagnosis.

Note that the above propositions show that multi agent diagnosis is possible. In particular, Proposition 5 offers the possibility to establish global diagnoses by information exchange between agents

The complexity of determining a global diagnosis depends on the organization of the multi agent system. First, knowledge of the system can be distributed in different ways over the agents. We will consider two extreme cases, knowledge that is either semantically of spatially distributed. Second, it makes an important difference whether agents use fault models of the behavior of components. Third, the dependencies between the knowledge distributions plays an important role. The dependencies determine whether agents have to exchange information to make a 'local' diagnosis.

Analysis

Dependent descriptions Before agents can establish a global diagnosis they first have to establish a local diagnosis using the knowledge of their part of the system. An important issue is whether they can do this independently of each other.

Dependencies arise because different models of the system are interconnected. By definition, such connections are present when knowledge is spatially distributed. When knowledge is semantically distributed, independence is possible, e.g., if a electrical and a thermodynamical description of the system is used. If, however, the heat of a (broken) component influences the electrical characteristics of the near by components, we no longer have independence.

We can enforce independence by observing the values of all connection points between different descriptions of the system; i.e. the values of Ex_i. In large systems this may not be feasible. Hence, agents have to exchange predicted values of connection point for every candidate diagnosis they consider. This may cause large communication overhead since the number of candidate diagnoses is exponential.

Exchanging information for each candidate diagnosis is not the only problem. If connection between incomplete models S_i of the system S are directional (i.e. all connection points in Ex_i are either inputs or outputs), the connections form graph that may contain *cycles*. Hence, the agents may need many cycles of exchanging predicted values in order to reach a stable prediction of the systems behavior. Moreover, because of numerical instabilities, the agents may not reach a stable prediction.

If not all connection are directional, the values of connection points in Ex_i cannot be determined by a single agent given a diagnosis. Two or more agents place constraints on the value of a connection point. An example of such a system is a battery and a lamp managed by two diagnostic agents, one for the battery and one for the lamp. The voltage and the current in the connection point depends on the characteristics of both the battery and the lamp. One may, for example, use bond graphs to create a model of the system with only explicit in- and outputs [3]. This is also possible for the battery-lamp example. The connections between the parts of the system managed by different agents, however, may form *cycles*.

Semantically distributed knowledge If knowledge is semantically distributed, each agents looks at different aspects of the whole system. We will first consider the situation in which agents have no fault model, and in which the knowledge of the agents is independent. The latter implies that either there are no connections, $Ex_i = \varnothing$, between the different descriptions of the system or all connection points of the connections between S_1 and S_2 are observed.

If we only apply consistency based diagnosis, i.e. $Obs_{\mathrm{abd}} = \varnothing$, we can derive the following result.

Proposition 6 *Let the diagnostic agents A_1 and A_2 be organized as described above and let D_1, D_2 respectively their diagnoses. Then, $D = \{mode(c, nor) \mid mode(c, nor) \in D_1, mode(c, nor) \in D_2\} \cup \{mode(c, ab) \mid mode(c, ab) \in D_1$ or $mode(c, ab) \in D_2\}$ is a single agent diagnosis.*

Note that if both D_1 and D_2 are minimal diagnoses, D need not be a minimal diagnosis.

The above proposition, together with Proposition 4, implies that we can determine all minimal diagnoses of a single agent approach combining every minimal diagnosis of agent A_1 with every minimal diagnosis of agent A_2 and subsequently select the minimal diagnoses from the resulting set. Since the number of combinations is quadratic in the number of minimal diagnoses, and assuming that the number of minimal diagnoses of each agent is polynomial in $|C|$, we are able to determine the global (single agent) diagnoses in polynomial time.

As in the single agent approach, we can improve consistency based diagnosis if we also allow for abductive explanation of normal observations [8]. The results of Propositions 2 and 3 can be extended to multi agent diagnosis.

Proposition 7 *Let the diagnostic agents A_1 and A_2 be organized as described above, let D_1^{abd} and D_2^{abd} be their abductive kernel diagnoses and D_1^{con} and D_2^{con} their consistency based kernel diagnoses. Then, $D = D_1^{abd} \cup D_2^{abd} \cup D_1^{con} \cup D_2^{con}$ is a single-agent kernel diagnosis if D is a partial diagnosis.*

Note that the above proposition and Proposition 3 imply that we can determine all kernel diagnoses of a single agent approach combining every abductive and consistency based kernel diagnosis of agent A_1 and A_2 and subsequently select the minimal consistent kernel diagnoses from the resulting set. Again, since the number of combinations is quadratic in the number of minimal diagnoses, and assuming the number of minimal diagnoses of each agent is polynomial in $|C|$, we can determine the global (single agent) diagnoses in polynomial time.

In some areas, it is important to know the type of fault that has occurred. In medical diagnosis for instance, we do not only need to know the component that is failing but also what is causing it to fail. In this area we usually do not replace a component but instead try to eliminate the cause of the malfunction. Hence, fault models are required.

Allowing for fault models complicates the process of combining the candidate diagnoses of several agents. The reason for this is that, given an ordering of candidate diagnoses $D_1 \prec D_2 \prec D_3 \prec D_4$, D_1 and D_3 can be diagnoses while D_2 and D_4 are not. Hence, we can no longer characterize an exponential number of diagnoses using a polynomial number of minimal or kernel diagnoses. Exchanging all (kernel) diagnoses between the agents is, in general, infeasible.

Instead of exchanging all diagnoses, we could use an incremental approach. In such an approach the agents start exchanging the diagnoses in the order of decreasing likelihood. They stop the moment they agree on the diagnoses of a certain likelihood. Since the a priori chance that a component is broken is in most situations very small, this approach might find the numerically minimal diagnoses in a reasonable amount of time.

We might improve the incremental approach if agents supply the reasons of rejecting a proposed diagnosis. When agent A_1 proposes a partial diagnosis D_1, agent A_2 might reject the diagnosis because some (combination of) modes is inconsistent with its observations. Let $R_2 \subseteq D_1$ be such (a combination of) modes. Then R_2 is the smallest subset of D_1 such that: $R_2 \cup Sd_2 \cup Ctx \cup Obs_2 \mid\!\sim \perp$. Agent A_1 can use this information R_2 as a constraint in its search for a next diagnosis. It may not select a new diagnosis D_1' containing R_2 as a subset.

Spatially distributed knowledge We assume that every part of the system managed by an agent has only explicit in- and outputs. If agents use fault models, they have to exchange information about the values of connection points connected to another agent for every candidate diagnosis they consider. The agents can reduce the amount of information exchange by ignoring the fault models. Agents may reduce the amount of information exchange even further if they may assume default values for these connection points. In both cases, we can only apply consistency based diagnosis or consistency based diagnosis with abductive explanation of normal observations.

Inputs of an agent's part of the system that are determined by other agents, can be incorrect. Therefore, agents must assume the correctness of these inputs and must be able to withdraw these assumptions during diagnostic reasoning. When an agent no longer assumes that an input is correct, it must pass on this information to the agent whose part of the system determines the input. For every candidate diagnosis an agent considers, it must provide this kind of feedback to the other agent(s). How to do this efficiently is an open question that requires further research.

5 Conclusion

Multi agent diagnosis is possible but not always feasible. If diagnostic knowledge is semantically distributed, the usage of fault models may result in exchanging an exponential amount of information in order to establish a global diagnosis. A proper coordination protocol may restrict the amount of information exchange.

If diagnostic knowledge is spatially distributed, the amount of information exchange depends on whether the agents exchange predicted values. Circular dependencies between the information required by different agents may cause a lot of information exchange. Moreover, the use of fault models makes things worse. An important topic for further research will be the development of protocols that enable establishing a global diagnosis while controlling the amount of information exchange.

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