TOWARDS A MULTIMODELING APPROACH OF DYNAMIC SYSTEMS FOR DIAGNOSIS

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Abstract: This paper presents the basis of a multimodeling methodology that uses a CommonKADS conceptual model to interpret the diagnosis knowledge with the aim of representing the system with three models: a structural model describing the relations between the components of the system, a functional model describing the relations between the values the variables of the system can take (i.e. the functions) and a behavioural model describing the states of the system and the discrete events firing the state transitions. The relation between these models is made with the notion of variable: a variable used in a function of the functional model is associated with an element of the structural model and a discrete event is defined as the affectation of a value to a variable. This methodology is presented in this paper with a toy but pedagogic problem: the technical diagnosis of a car. The motivating idea is that using the same level of abstraction that the expert can facilitate the problem solving reasoning.

1 INTRODUCTION

This paper is concerned with the design of knowledge based systems to supervise, diagnose and control industrial process. The dynamic aspect of industrial processes poses the difficult problem of the acquisition and the representation of the underlying temporal knowledge which is often mixed with other types of knowledge (Basseville and al, 1996).

To solve these problems, we first focus our works on the multi model based diagnosis approach (Chittaro and al, 1993) with the aim of designing models at the same level of abstraction level than the experts. Second, we want that the model formalisms to be adequate to represent the temporal knowledge coming from both from Experts and from the learning algorithms of the Stochastic Approach of (Le Goc et al, 2005). And three, we want the interpretation knowledge to closed to the cognitive tasks the models are made for and we propose to use a generic conceptual models. So, section 2 of this paper positions shortly our approach according to the main modelling approaches for diagnosis. Section 3 presents the basis of our methodology through its application to a toy but pedagogic problem: the technical diagnosis of a car. Finally, section 4 states our conclusions and perspectives.

2 MODELLING APPROACHES

The limitations and the problems (Dagues, 2001) of the heuristic approach (Clancey, 1985) has motivated the Model Based Diagnosis approach (MBD) where the knowledge about the system is represented in a unique logical model (Reiter, 1987).

The MBD approach use of a unique model of the system to be diagnosed containing the knowledge about both the structure (components and interconnections) and the behavior of the system (relations between the values of the input and the output of the components). This model generally comes from the design model of the system so that it contains a lot of components leading to computational difficulties for the diagnosis task (the number of potential diagnosis is exponential with the number of components). This problem is crucial and has motivate a large amount of works to reduce the size of the space search. But more, this model contains nothing about the evolution of the values of the variables over time and nothing to represent the knowledge about the state of the system. This is a crucial lack when diagnosing a dynamic system where the observations are timed.

The Multi Model Based Diagnosis (MMBD) has been proposed to avoid these problems (Chittaro and al, 1993). This approach defines four models linked

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each other to describe the system to diagnose (cf. (Zouaoui, 1998) and (Thetiot, 1999) for examples). The first one is the Structural Model that describes the components constituting the system and how they are connected each other. The second model is the Behavioral Model describing how components work in terms of the physical laws linking quantities. These two models represent the fundamental knowledge. The third model is the Functional Model describing the different roles the components may play in the physical processes in which they take part. The concept of function is the basis of the description of the functional roles, the processes and the phenomena that provides an interpretation of the fundamental knowledge. The goals assigned to the system by its designer(s) are described in the last model, the Teleological Model. These two last models refer to the interpretation knowledge. Indeed, the MMBD is still concerned with the computational problem of the diagnosis linked with the number of the components declared in the structural model (Zouaoui, 1998). This problem is directly connected to the abstraction level which is still defined by the designer(s).

3 MODELLING WITH EXPERTS ASSUMPTIONS

So, our works is based on the hypothesis that an expert uses a set of models at a level of abstraction that allows efficient diagnosis reasoning and this level of abstraction is directly linked with the diagnosis task, not the design task.

We propose to use a CommonKADS conceptual model (Schreiber and al, 2000) to interpret a knowledge source with the aim of representing the system with three models (Zanni and al, 2005): a structural model describing the relations between the components of the system, a functional model describing the relations between the values the variables can take (i.e. mathematical functions) and a behavioural model describing the states of the system (corresponding to the operating modes of (Chittaro and al, 1993)) and the discrete events firing the state transitions. The relation between these models is made with the notion of variable: a variable used in a function of the functional model is associated with an element of the structural model and a discrete event is defined as the affectation of a value to a variable.

Figure 1: Typical Binary Relation.

We define a model as an organized set of binary relations $B(S_l, S_r)$ between symbols S_i denoting objects described in the domain ontology of the conceptual model of the knowledge. A binary relation $B(S_i, S_j)$ is also denoted with a symbol (i.e. *B*). Such a binary relation only means that there exist a link between the objects denoted with the symbols S_i and S_j. A typical graphical representation of a binary relation is provided in Figure 1, where nodes are boxes or circles and the relation is eventually represented with an ellipse. When useful, the arcs can be oriented to show the orientation of a flow like typically a flow of energy, material or information.

A model can then be represented with a graph where nodes are symbols and arcs are relations. Basically, a node symbol denotes a component or an aggregate of components (i.e. a structure) in a structural model, a variable in a functional model or a state in a behavioural model. An arc represents a link between two nodes. Such a link can be a connection link between two structures in a structural model, an information link between the values of variables in a functional model or a transition between two states in a behavioural model. Consequently, a binary relation in a structural model represents a connection between two structures; a mathematical function in a functional model and a transition between two states in a behavioural model. It is to note that a set of binary relations with the same right node symbol can be aggregated in a single n-ary relation when this aggregation is meaningful (an arithmetical function between 3 variables for example).

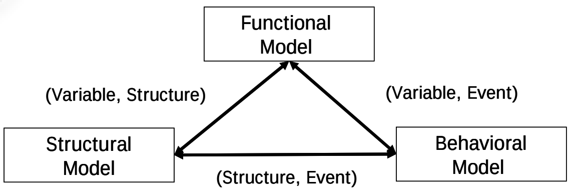

Figure 2: Links between the three models.

With this simple formalism, a structural model is an organised set of physical relations between components or aggregates, a functional model is an organised set of logical relations defining the values of a variable given those of a set of variables, and a behavioural model is a set of sequential relations between states. These sequential relations can be conditioned with predicates concerning the occurrence of discrete events. A discrete event is defined according to spatial discretization principle of the Stochastic Approach (Le Goc et al, 2005) as a couple *(x, i)* where *x* is a symbol denoting a variable and *i* is a value for *x* so that a discrete event occurrence is triplet (x, i, t_k) meaning: $x(t_k)=i$.

The modelling is based on three principles. The first is that each object symbol S_i used in one of the three models denotes a concept that is defined at the domain level of a CommonKADS model. This means that the introduction of an object symbol that is not associated with an element of the knowledge domain model is prohibited. This model provides then the means for interpreting the three models. The second principle is that a variable is always associated with a component or an aggregate defined in the structural model. The values a variable can take are provided either from its associated components (input variable) or are computed with a function defined in the functional model. And the third principle is that a transition between two states is conditioned either with the time elapsed in a state (autonomous transition) or with a logical formula linking the occurrences of discrete events. The notion of variable constitutes then the common point of the three models (Figure 2), providing a means to the consistency analysis of the models.

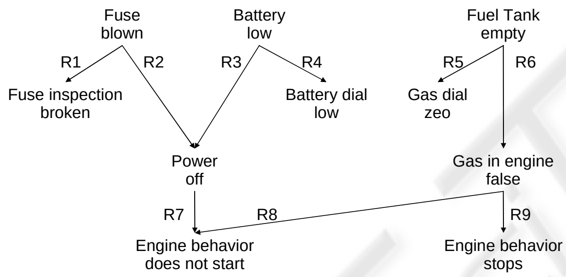

Figure 3: An example of a knowledge base.

4 APPLICATION

To illustrate the modelling process using these principles, let us take the example providing from (Schreiber et al, 2000) of the (simple) knowledge base used to diagnose a car.

Figure 3 proposes a graphical representation of the set $R=\{R_i(P_c, P_e)\}$ of the nine rules constituting the knowledge base. In this graph, a rule $R_i(P_c, P_e)$ denote a logical consequence relation from a proposition P_c to another P_e. This logical relation is used to represent a causal relation between a cause (*Fuel Tank empty*) and an effect (*Gas in engine false*). To interpret this knowledge, we will use the classical and minimal CommonKADS diagnosis template «hypothesis generation and hypothesis discrimination» (Zanni and al, 2005). This template (Figure 4) considers the diagnosis reasoning as being made of two basic inferences, one to generate the hypothesis from the observed behaviour and the second to discriminate between the different hypotheses according to the observed behaviour.

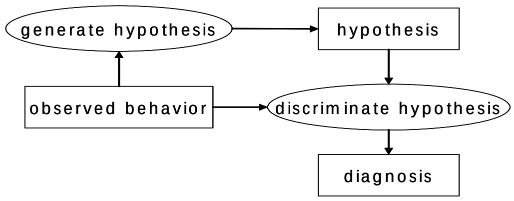

Figure 4: The Diagnosis Template.

This template allows the classification of the propositions contained in the knowledge base in a set of observed behaviour (*Fuse inspection broken*, *Engine behaviour does not start*, *Engine behaviour stops*, *Battery dial low* and *Gas dial zero*) and a set of hypothesis (*Fuse blow*, *Battery low*, *Fuel Tank empty*, *Power off* and *Gas in engine false*). The observed behaviour set contains the complains that motivate the diagnosis reasoning (*Engine behaviour does not start*, *engine behaviour stops*). This functional classification of the propositions leads to distinguish a first set of rules *S1={R1, R4, R5}* that allows to observe unobservable states of the car from the second set of rules *S2={R2, R3, R6, R7, R8, R9}* that expresses the propagation of an unobservable car state (*Fuse blow*, *Battery low*, *Fuel Tank empty*) to another unobservable car state (*Power off*, *Gas in engine false*) and finally, to the complains. So the propositions of R can be interpreted as binary relations between a variable (*Fuel Tank* for example) and a value (*empty*): each proposition corresponds to a predicate *Equal(Variable, Value)*. Consequently, a rule is an instantiation of a second order relation of the form *Cause(xi=v1, xj=v2)* where the symbol "=" denotes the predicate *Equal*, *xi* and *xj* denote a variable and *v1* and *v2* two values. This relation means then that there exist a logical relation between the fact *xi=v1* and *xj=v2* (i.e. a logical rule *xi=v1⇒xj=v2*) and supposes that there exists a physical relation between the variables *xi* and *xj* that is to say between the components or the aggregates *ci* and *cj* the variables *xi* and *xj* are linked with. The set *X={xi}* of symbol variable associated with the set *C={ci}* of symbol components can then be build, and the knowledge base *R* can then be rewritten as follow:

- R1: If x1=Blown Then x4=Broken
- R2: If x1=Blown Then x7=Off
- R3: If x2=Low Then x7=Off
- R4: If x2=Low Then x5=Low
- R5: If x3=Empty Then x6=Zero
- R6: If x3=Empty Then x8=False
- R7: If x7=Off Then x9=Does_not_start
- R8: If x8=False Then x9=Does_not_start

- R9: If x8=False Then x9=Stops

From these items, a set of connection relations of the form *ConnectedTo(ci, cj)* can be deduced and represented in the structural model of figure 5. The symbol components *electric_alimentation* and *gas_alimentation*, respectively associated with the variables *Power* and *Gas_in_engine*, denotes abstract aggregates of components. Similarly, the set of underlying rules $xi=v1 \Rightarrow xj=v2$ can be deduced. When defining the domain set of value for each variables, each rule $xi=v1 \Rightarrow xj=v2$ subsumes a function of the form $xj=f(xi)$ at least defined when $xi=v1$ and $xj=v2$. When two functions $xj=fi(xi)$ and $xj=fk(xk, xj)$ share the same output variable *xj*, a new function $xj=fj(xi, xk)$ can be defined. In the functional model of figure 6, a rectangle (node) specifies a variable name and an ellipse (relation) specifies a function names. When the value set of each variable *xi* can be defined, the set $F=\{fi\}$ of functions *fi* can be entirely specified with tables of values. When a value is missing, it is always possible to define the missing value as the complement of the known values. For example, the value set of the variable *x1* is {*Blown*, *not_Blown*}. The tables of figure 7 are formulated independently of the variables, when using the notation *o(f)* and *i(f)* to denote the value of the output and the input of the function "*f*".

To introduce the behavioural model, let us consider the variable *x9* associated with the aggregate *c9* (*engine*). The value set of *x9* is {*Off*, *On*} where *Off* means either *stops* or *does not start*. The complains *x9=Off* can then be interpreted as an undesirable car state and so, the predicate *x9=On* corresponds to the desirable car state "the car is working". According to the set of rules *R*, the car stay in this state until the occurrence of a discrete event *No_power* (*x7=Off*) or *No_gas* (*x8=False*). In this case, the car transit from a state *Working* to a state *Out of Power* or *Out of Gas*, which are by definition two transient states. As soon as the inertia will have no effect, the car will stops in a *Failure* state. When the ignition key will be off, the car will be in a *Broken down* state where *x9=Off*: a repairing action is required to bring back the car in a normal *Stop* state. This analysis leads to the behavioural model of Figure 8, which is a finite state machine represented with the DEVS formalism (Le Goc et al, 2006). This formalism is compatible with the formalism of Figure 1: nodes (circles) are states and links are state transitions. Autonomous transitions (between *Out of Gas* and *Failure*) are represented with dashed lines. An autonomous transition is fired when the elapse time in a state *qi* is greater than the maximum duration ΔTi of the *qi* state.

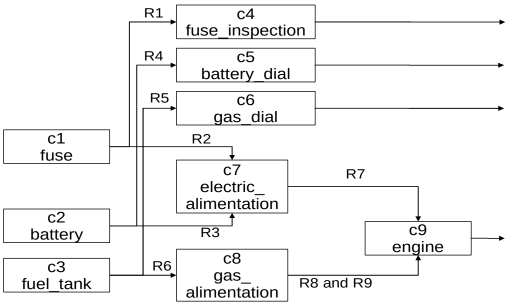

Figure 5: Structural model.

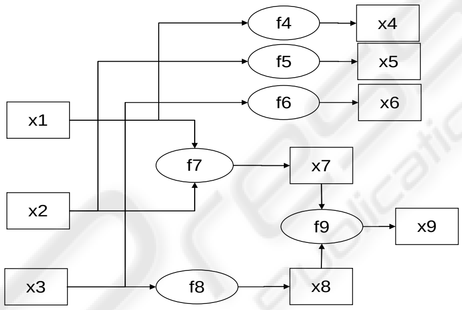

Figure 6: Functional model.

o(f6)=f6(i(f6))	
i(f6)	o(f6)
Empty	Zero
Not_Empty	Not_Zero

o(f8)=f8(i(f8))	
i(f8)	o(f8)
Empty	False
not_empty	True

o(f7)= f7(i1(f7), i2(f7))		
i1(c7)	i2(f7)	o(f7)
not_blown	not_low	On
not_blown	Low	Off
Blown	not_low	Off
Blown	Low	Off

o(f9)= f9(i1(f9), i2(f9))		
i1(f9)	i2(f9)	o(f9)
On	True	Start
On	False	Does_not_start
Off	True	Does_not_start
Off	False	Does_not_start

Figure 7: Specification of the functions.

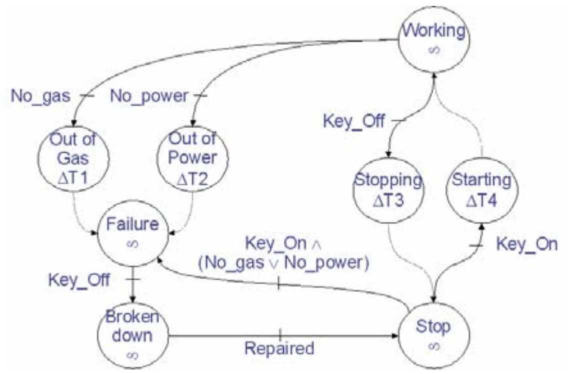

Figure 8: Behavioural model.

The models of figures 5, 6, 7 and 8 are implicitly contained in the initial knowledge base of figure 3, but the behavioural model is the most "covered". Such an observation is very frequent because the dynamic properties are generally misunderstood. For example, the difference between the values *stops* and *does not start* becomes clear only when considering the role of the ignition key in the behavioural model. It is to note also that the behavioural model is made of two parts: one part (at the right of figure 8) describes the normal working of the car (*Working*, *Stop*, *Starting* and *Stopping* states), and the second part (at the left of figure 8) describes the abnormal working of the car. Such a notion can not be defined with the functional model because it is defined as an organized set of relations between values of variables. This means that when considering dynamic systems, the normal behavioural model notion of Reiter's diagnosis theory for static systems has been shifted in the classification of the system states in normal and abnormal categories. This leads to design a new algorithm for diagnosing dynamic systems.

(f7)= f7(i1(f7), i2(f7		
i1(c7)	i2(f7)	o(f7)
T	T	T
T	F	F
F	T	F
F	F	F

Figure 9: The f_7 function as an "AND" function

5 USING THE MODELS

The structural and functional models of figures 5, 6 and 7 can be used in Reiter's diagnosis theory with a simple logical transcription in the first order predicate logic. The set of components COMPS is deduced from the structural model: COMPS={c1, c2, c3, c4, c5, c6, c7, c8}

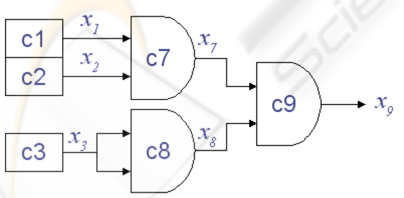

Figure 10: The nine rules as a logical circuit.

The system description SD is deduced from the functional model when associating each function f_i with the component c_i corresponding to the output variable of the function f_i. For example, the function f_7 is associated with the component c_7 through the variable x_7: $x_7=o(f_7)$. Next, the symbols used to specify the functions f_i must be represented with the Boolean symbols *T* for *True* and *F* for *False*. For example, when rewritten the symbols *not_Blown*, *not_Low* and *Off* as *T* and the symbols *Blown*, *Low* and *Off* as *F*, the function f_7 become the logical function *AND* (Figure 9). The same is true for the functions f_8 and f_9. Finaly, when considering the components c_4, c_5 and c_6 as sensors that can not failed, this lead to consider the following logical circuit of Figure 10. The system description is then:

SD = {
¬AN(x)∧FUSE(x) ⇒ o(x)=Not_blown,
¬AN(x)∧BATTERY(x) ⇒ o(x)=Not_low,
¬AN(x)∧FUEL_TANK(x) ⇒ o(x)=Not_Empty,
¬AN(x)∧AND_GATE(x) ⇒ o(x)=AND(i1(x), i2(x)),
//Component type declaration
FUSE(c1), BATTERY(c2), FUEL_TANK(c3), AND_GATE(c7), AND_GATE(c8), AND_GATE (c9),
//Connexions
o(c1)=i1(c7), o(c2)=i2(c7), o(c3)=i1(c8), o(c3)=i2(c8), o(c7)=i1(c9), o(c8)=i2(c9)
}

This model is not efficient for diagnosing because, given the observations *engine behaviour stops* or *engine behaviour does not start*, all the six components will be suspected. Adding observation as *Gas dial zero* reduces the problem, but to the three components *c7*, *c8* and *c9*, which can be abnormal also.

Now, let us suppose that at time t_k, the system is in the *Working* state (Figure 8). The observation *Gas dial zero* will be represented with the discrete event occurrence (t_k, x_6, *zero*) (i.e. $x_6(t_k)=zero$). The functional model provides the relations: $x_6=f_6(x_3)$ and $x_8=f_8(x_3)$. Given the functional model (figures 6 and 7), $x_6(t_k)$=zero implies $x_3(t_k-\tau_6)$=empty and $x_8(t_k-\tau_6+\tau_8)$=false corresponding to the occurrence of the discrete event *No_gas*, where τ_6 and τ_8 are the time transfer of functions f_6 and f_7. The behavioural model of Figure 8 shows then that the system will transit from state *Working* to the state *Out of gas* at time $t_k-\tau_6+\tau_8$, and finally in the state *Failure* at time $t_k-\tau_6+\tau_8+\Delta T_1$. So, if at time $t_n>t_k$, the observation *engine behaviour stops* is made on the car with $t_n \approx t_k-\tau_6+\tau_8+\Delta T_1$, the observation *Gas dial zero* at time t_k can be used to infer that the cause of this complain is the fact that the fuel tank is empty since $t_k-\tau_6$.

This example shows that a diagnosis algorithms adapted to the reasoning with timed observations is required. The difficulty of this problem can be perceived trough the formulae "$t_n \approx t_k-\tau_6+\tau_8+\Delta T_1$". The symbol ≈ denotes a temporal equality predicate that is generally interpreted as the fact that the time t_n belongs to a timed interval containing the time "$t_k-\tau_6+\tau_8+\Delta T_1$". The basic but fundamental problem is then to define these intervals. The Stochastic Approach for learning timed relations between discrete events proposes a solution to this problem

(Le Goc and al, 2005). This is the reason why one of the main requirements for our modelling approach is to be compatible with this approach of learning.

6 CONCLUSION

This paper presents the basis of a multimodeling methodology that uses a CommonKADS conceptual model to interpret the knowledge source with the aim of representing the system with three models: a structural model describing the relations between the components of the system, a functional model describing the relations between the values the variables of the system can take (i.e. the functions) and a behavioral model describing the states of the system and the discrete events firing the state transitions. The relation between these models is made with the notion of variable: a variable used in a function of the functional model is associated with an element of the structural model and a discrete event is defined as the affectation of a value to a variable.

This methodology is presented in this paper with a toy but pedagogic problem: the technical diagnosis of a car with a given knowledge base (Schreiber and al, 2000). This example shows that the resulting models are compatible with Reiter’s theory of diagnosis and that a specific reasoning is required to take advantage of the behavioural model of the dynamic system to diagnose. Such reasoning must take into account the time of the observations. This example illustrates clearly our goal: making explicit the models used by experts to formulate their knowledge. The idea is that using the same level of abstraction that the expert can facilitate the problem solving reasoning. This method has been applied to a real world dynamic system, the Cubblize dam, confirming the conclusions presented in this paper and validating the method (Masse and Le Goc, 2007). It is to note finally that the resulting models can be used either fore the design or the simulation phases.

Our current work aims at formalizing the global methodology and to design of a diagnosis algorithm able to use a behavioural model that can be built according to the timed relation the Stochastic Approach of knowledge learning discovers.

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