TIMED OBSERVATIONS MODELLING FOR DIAGNOSIS METHODOLOGY
A Case Study

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Abstract: The TOM4D methodology is based on constructing models at the same level of abstraction that experts use to diagnose a process; thus, the resultant models are more simple and abstract allowing a more efficient diagnosis. For this purpose, the framework CommonKADS to interpret and organize the available knowledge of experts is combined with a multi-modelling approach in order to describe the knowledge. This paper complements works accomplished previously about TOM4D, introducing the combined use of Formal Logic and the Tetrahedron of States in order to build models more suitable for the diagnosis task. Formal Logic provides a logical interpretation of expert's reasoning. The Tetrahedron of States provides a physical interpretation of the process variables and allows to exclude of the logical model those states physically impossible.

1 INTRODUCTION

Knowledge-based diagnosis of systems deals with the difficulty of knowledge acquisition and representation. The main problem is to determinate the right level of abstraction in which the models have to be constructed to obtain an efficient diagnosis. Most modelling approaches use the abstraction level of the available models, generally design models. However the abstraction level of the design task requires the definition of a lot of components, some of which might be meaningless in the diagnosis task. This results in a hight computational cost since the number of possible diagnosis increases exponentially with the number of components.

TOM4D (Timed Observations Modelling For Diagnosis) (Goc and Masse, 2007; Goc et al., 2008) is a modelling methodology based on the idea that experts use implicit models to formulate their knowledge about a process and the way of diagnosing it. Such models only consider components that are concerned with a diagnosis and thus, the number of components is minimal allowing a more efficient diagnosis.

This paper completes the TOM4D modelling process presented in (Goc et al., 2008) to propose the construction of two models that complement each other: a logical model that provides a reasoning model consistent with the Reiter's theory (Reiter, 1987) and a physical model that provides a physical dimension to the process variables and so, defines its physical structure. This latter allows to identify those states that, although they are valid in the logical model, are physically impossible.

The next section provides a brief overview of the main modelling approaches and the major difficulties that they present. Section 3 presents a case study on the use of Formal Logic and the Tetrahedron of States (ToS) (Chittaro et al., 1993) to define a logical model and a physical model which complement each other and are presumably close to those models that experts build to carry out a diagnosis. Finally, section 4 states our conclusions and perspectives.

2 MODELLING APPROACHES FOR DIAGNOSIS

The diagnosis of malfunctioning of devices or systems is a research area of Artificial Intelligence since the decade of the seventies. Different approaches (Zanni, 2004), such as heuristic reasoning (Clancey, 1985), Model-Based Diagnosis (MBD) (Reiter, 1987; Dagues, 2001) and Multi Model Based Diagnosis

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(MMBD) (Chittaro et al., 1993), have arisen from that time to the present. However, diagnostic reasoning approaches present, in general, two major drawbacks (Goc and Masse, 2007; Goc et al., 2008). First, the large number of components of the resulting model leads to computing difficulties in the diagnosis task. That is to say, the number of possible diagnoses grows exponentially with the number of components. This problem is directly connected to the level of abstraction used. These models generally come from the design model which has nothing to do with knowledge model to diagnosis. Second, even when the system has few components, the consistency based theory of diagnosis provides no means to eliminate diagnoses which are logically acceptable but meaningless.

TOM4D (Goc and Masse, 2007; Goc et al., 2008) is a modelling methodology for dynamic systems based on the hypothesis that an expert uses a set of models at a level of abstraction that allows efficient diagnostic reasoning, and this level is directly linked with the diagnosis task, not with the design task. This methodology proposes to combine the modelling of the experts' cognitive process, using CommonKADS (Breuker and de Velde, 1994; Schreiber et al., 2000), with a multi-modelling approach for dynamic systems (Chittaro et al., 1993; Chittaro and Ranon, 1999), in order to try to get around the aforesaid problems.

3 TOM4D: INTERPRETATION MODELS

The TOM4D modelling process (Goc et al., 2008), shown in Figure 1, aims to produce a generic model of system, from the available knowledge and data, in order to obtain a suitable model for the diagnosis task. This modelling process consists of three fundamental phases: **knowledge interpretation**, whose objective is organizing and interpreting the available knowledge; **process definition** where the boundary of the process that governs the system, operating goals and normal and abnormal operating modes are defined; and **generic modelling**, in which the aim is to define a more general and more abstract model. This modelling process is generally cyclical and each stage can require to return to previous phases with the objective of revising expert's knowledge, results, ideas, modelling decisions, etc. We shall focus our attention on how, in the second and the third phases, Logic Formal and the ToS can be used as interpretation paradigms in order to carry out a logical interpretation and a physical interpretation of the process.

Figure 2 depicts the domain concerning the diagnosis of problems with a car that the authors of

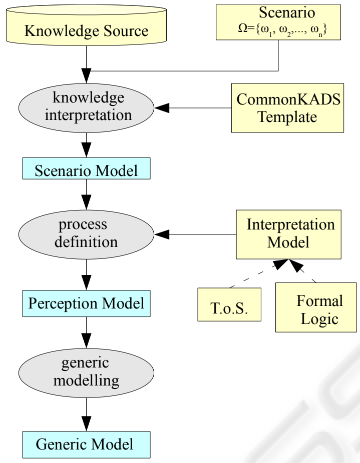

Figure 1: TOM4D modelling process.

(Schreiber et al., 2000) introduce in their book. The figure presents nine rules of knowledge, noted as $R_1,..,R_9$, whose meaning is, for example: R_1 indicates that *if the fuse is blown then the result of the fuse inspection is broken*.

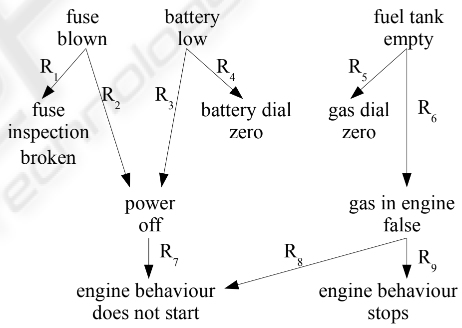

Figure 2: Knowledge pieces in the car-diagnosis domain.

We shall suppose that the components associated with concepts *fuse inspection*, *battery dial* and *gas dial* work properly. Therefore, the variables and components considered in the modelling process are listed below and rewritten as x_1, x_2, x_3, x_7, x_8, x_9 and c_1, c_2, c_3, c_7, c_8, c_9, respectively.

$x_1 \equiv$ `fuse.status`	$c_1 \equiv$ `fuse`
$x_2 \equiv$ `battery.status`	$c_2 \equiv$ `battery`
$x_3 \equiv$ `fuel-tank.status`	$c_3 \equiv$ `fuel-tank`
$x_7 \equiv$ `power.status`	$c_7 \equiv$ `electric supply`
$x_8 \equiv$ `gas-in-engine.status`	$c_8 \equiv$ `gas supply`
$x_9 \equiv$ `engine-behaviour.status`	$c_9 \equiv$ `engine`

The rules R_8 and R_9 establish fuzzy knowledge since the value of x_9 is indeterminate; that is, if $x_8 = false$, then $x_9 = does\_not\_start \wedge x_9 = stops$. In order to eliminate this ambiguity, we shall interpret and rewrite the values $does\_not\_start$ and $stops$ as $\neg works$; that is to say, if $x_8 = false$ then $x_9 = \neg works$. Therefore, the values that the variables can assume are the following ones: $x_1 \in \{blown, \neg blown\}$, $x_2 \in \{low, \neg low\}$, $x_3 \in \{empty, \neg empty\}$, $x_7 \in \{off, \neg off\}$, $x_8 \in \{false, \neg false\}$, $x_9 \in \{works, \neg works\}$.

From the modelling process and analysis on this example presented in (Goc and Masse, 2007), a representation by means of logical gates of the process is possible, as Figure 3 shows.

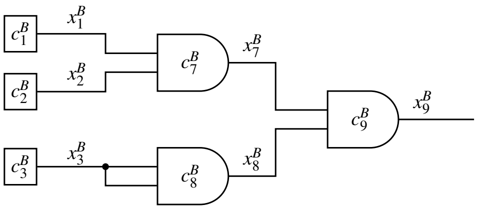

Figure 3: Logical model of the process.

The process variables $x_1, x_2, x_3, x_7, x_8, x_9$ are then interpreted as binary variables $x_1^B, x_2^B, x_3^B, x_7^B, x_8^B, x_9^B$ respectively, which take values 1 ($true$) or 0 ($false$). For example, $x_1 = blown$ is logically interpreted and represented as $x_1^B = 0$, $x_1 = \neg blown$ is represented as $x_1^B = 1$, and so on for each variable. Consequently, each component c_i, $_{i=1,2,3,7,8,9}$ is interpreted as a logical gate c_i^B $_{i=1,2,3,7,8,9}$ in Figure 3. For example, R_2, R_3 allow to write $x_1^B = 0 \vee x_2^B = 0 \Rightarrow x_7^B = 0$ and to define $x_7^B = and(x_1^B, x_2^B)$, which is the functional model of the component c_7^B.

This logical interpretation leads to build a logical model according to the consistency-based diagnosis theory of (Reiter, 1987) as a set of first order predicate formula. The problem with Reiter's theory is that it subsumes that logically consistent states corresponds to normal (desired) behaviours and the inconsistent states to abnormal (undesired) behaviour denoting a problem with at least one component. But this correspondence does not resist with a physical interpretation of the states. For example, the consistent state $x_1^B = 0, x_2^B = 1, x_3^B = 1, x_7^B = 0, x_8^B = 1, x_9^B = 0$ describes a normal behaviour that is not desirable: the *fuse* is *blown* and the *engine does not work*. The inconsistent state $x_1^B = 0, x_2^B = 0, x_3^B = 1, x_7^B = 0, x_8^B = 0, x_9^B = 0$ is abnormal (the tank has fuel ($x_3^B = 1$) but there is not gas in engine ($x_8^B = 0$)) and corresponds to a problem with the gas supply (component c_8^B). In contrast, the inconsistent state $x_1^B = 0, x_2^B = 0, x_3^B = 0, x_7^B = 0, x_8^B = 1, x_9^B = 0$ (the fuel tank is empty and there is gas in the engine) can not be associated with a problem of a component: it is a transient state that is a normal behaviour.

These examples shows that the logical interpretation of the variables that is required by Reiter's theory must be completed with a physical interpretation. For this purpose, (Chittaro et al., 1993) proposes to use ToS: in our example, the Hydraulic ToS and the Electric ToS will be used (Figure 4). So, with the TOM4D methodology, each variable x_i of the process is mapped both with a logical variable x_i^B and a physical variable x_i^P of the corresponding ToS. For example, using the Hydraulic ToS, the variable x_3 (fuel tank status) is associated with the gas volume $V(t)$ in the tank so that $x_3^B = 0$ is interpreted as $V(t) = 0$ ($x_3 = empty$) and $x_3^B = 0$ is interpreted as $V(t) \neq 0$ ($x_3 = \neg empty$). The variable x_8 (gas supply status) is associated with the gas flow $Qv(t)$ in the gas supply so that $x_8^B = 0$ is interpreted as $Qv(t) = 0$ ($x_8 = false$) and $x_8^B = 1$ is interpreted as $Qv(t) \neq 0$ ($x_8 = \neg false$). Similarly, the Electric ToS allows the following associations: x_2 (battery status) corresponds to the electric charge $Q(t)$ in the battery, x_1 (fuse status) with the system resistance $R(t)$, x_7 (electric supply status) with the voltage $U(t)$. In this interpretation phase, the functions of time $F(t)$ corresponding to a variable x_i are defined over $\Re$. Now to interpret the process behaviour and the correspond states, we assume that the current $I(t)$, the voltage $U(t)$ and the resistance $R(t)$ are piecewise constant over time: $I(t) = i_c$ or $I(t) = 0$ (no current), $U(t) = u_c$ or $U(t) = 0$ (no voltage) and $R(t) = r_c$ or $R(t) = \infty$ (the fuse is blown). Thus, $x_1 = blown$ ($x_1^B = 0$) means $R(t) = \infty$ and $R(t) = r_c$ otherwise, and $x_7 = off$ ($x_7^B = 0$) means $U(t) = 0$ and $U(t) = u_c \neq 0$ otherwise. Since $I(t) = \frac{dQ(t)}{dt}$, when $I(t)$ is zero, the electric charge of the battery is a constant: $x_2 = low$ ($x_2^B = 0$) means $Q(t) = q$ and otherwise $Q(t)$ evolves over time.

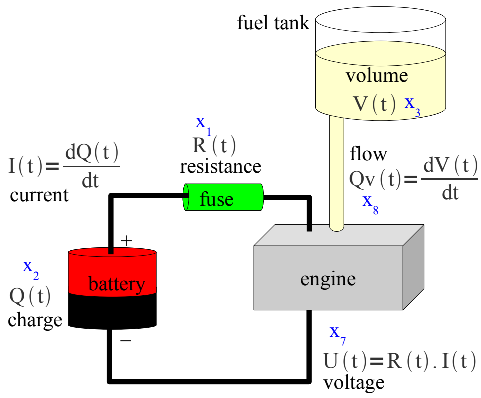

Figure 4: Physical model of the process.

The physical interpretation with through the ToS allows to provide a semantic to each states and to identifies those that are useful for diagnosis. For example, because $Qv(t) = dV(t)/dt$, all the states where $x_3^B = 0$ and $x_8^B = 1$ corresponds to a transitory situation: the fuel tank is empty ($V(t) = 0$) but there is still a fuel flow in the engine ($Qv(t) \neq 0$). We can then assume that $\exists t_k \in \Re$ so that: $\forall t \geq t_k, V(t) = 0 \Rightarrow Qv(t) = 0$. This interpretation allows to consider that $x_3 = empty \Rightarrow x_8 = false$ and hence, $x_3^B = 0 \Rightarrow x_8^B = 0$. Consequently, each states containing $x_3^B = 0$ and $x_8^B = 1$ can be removed from the logical model.

Similarly, the logical states $x_2^B = 0$ (battery is low) and $x_7^B = 1$ (electric supply is on) can be removed: $\exists t_k \in \Re, \forall t \in \Re, t \geq t_k,\ Q(t) = q \Rightarrow I(t) = 0$. Because $U(t) = R(t).I(t)$, this rule can be rewritten: $Q(t) = 0 \Rightarrow U(t) = 0$. Then, all states where $Q(t) = 0$ and $U(t) \neq 0$ are not usefull for diagnosis, and all states where $x_2^B = 0$ and $x_7^B = 1$ can be eliminate of the logical model. The same reasoning can be done with the resistance ($R(t) = \infty \Rightarrow U(t) = 0$) so that all states where $x_1^B = 0$ and $x_7^B = 1$ can be eliminated of the logical model. In our example, the physical interpretation of the variables allows to reduce the $2^6 = 64$ states of the logical model to 16 interesting states for diagnosis.

As a consequence, the TOM4D methodology considers that to build a generic model of a process, the expert's knowledge must be interpreted both in logical and physical terms. The logical model (Figure 3) describes the structure of the expert's diagnosis reasoning and the physical model (Figure 4) provides the diagnosis knowledge required for this reasoning. So both logical and physical models are necessary and complement each other. These models are, ultimately, those "constructed" by experts to do the diagnosis tasks. In practice, the combination of these two models simplify the diagnosis task.

4 CONCLUSIONS

The present paper complements the works presented in (Goc and Masse, 2007; Goc et al., 2008) about TOM4D, introducing a case study that verifies the main hypothesis of TOM4D: experts use implicit models to formulate their knowledge about a process and the way of diagnosing it, these models belong to a level of abstraction linked with the diagnosis task but not with the design task. The combination between Formal Logic and the ToS allows to build models close to those constructed by experts. The former provides a logic reasoning mechanism, the latter allows to discriminate the states having a meaning according to the diagnosis task and thus, to reduce the state space to only those concerned with the diagnosis.

Our current work focus on relating TOM4D with a method to discover experts' knowledge from sequence of discrete event occurrences registered by a machine. Linking this two approaches would allow to define a modelling process which takes experts' knowledge and data recorded by a machine and produces models useful to diagnosis.

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